Titre: Title:	Transportation Optimization in Tactical and Operational Wood Procurement Planning
Auteur: Author:	James Gregory Rix
Date:	2014
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Rix, J. G. (2014). Transportation Optimization in Tactical and Operational Wood Procurement Planning [Thèse de doctorat, École Polytechnique de Montréal]. PolyPublie. https://publications.polymtl.ca/1622/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/1622/
Directeurs de recherche: Advisors:	Louis-martin Rousseau, & Gilles Pesant
Programme: Program:	Mathématiques de l'ingénieur

UNIVERSITÉ DE MONTRÉAL

TRANSPORTATION OPTIMIZATION IN TACTICAL AND OPERATIONAL WOOD PROCUREMENT PLANNING

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THÈSE PRÉSENTÉE EN VUE DE L'OBTENTION
DU DIPLÔME DE PHILOSOPHIÆ DOCTOR
(MATHÉMATIQUES DE L'INGÉNIEUR)
DÉCEMBRE 2014

UNIVERSITÉ DE MONTRÉAL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

Cette thèse intitulée :

TRANSPORTATION OPTIMIZATION IN TACTICAL AND OPERATIONAL WOOD PROCUREMENT PLANNING

présentée par : RIX James Gregory
en vue de l'obtention du diplôme de : Philosophiæ Doctor
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ACKNOWLEDGEMENTS

First, I would like to thank my supervisors, Louis-Martin Rousseau and Gilles Pesant. This thesis could not have been completed without their knowledge, support, and perhaps most importantly patience. I want to acknowledge Jean-Marc Frayret and Michel Gendreau for agreeing to serve on my jury and carefully review my thesis. Finally I wish to thank Leandro Coelho for agreeing to serve as my external examiner and adapting his busy schedule to fit my thesis defense. This is an exceptional group of professors with whom it has always been a pleasure to work.

FPInnovations has played a vital role in this thesis, both financial and collaborative, over the course of my doctoral internship with their Value Maximization and Decision Support group. Their assistance in problem formulation, meeting with member companies, data collection, and development of an aesthetic and usable tool can not be understated. I wish to specifically thank Jean Favreau for leading this initiative, and Dave Lepage and Samir Haddad for their integral roles in development, testing, and debugging.

I also acknowledge the Natural Sciences and Engineering Research Council of Canada (NSERC), the Fonds de Recherche du Québec - Nature et Technologies, and the NSERC Value Chain Optimization Network for their financial support.

RÉSUMÉ

L'économie canadienne est dépendante du secteur forestier. Cependant, depuis quelques années, ce secteur fait face à de nouveaux défis, tels que la récession mondiale, un dollar canadien plus fort et une baisse significative de la demande de papier journal. Dans ce nouveau contexte, une planification plus efficace de la chaîne d'approvisionnement est devenue un élément essentiel pour assurer le succès et la pérennité du secteur.

Les coûts de transport représentent une dépense importante pour les entreprises forestières. Ceci est dû aux grands volumes de produits qui doivent être transportés sur de grandes distances, en particulier dans le contexte géographique d'un grand pays comme le Canada. Même si les problèmes de tournée de véhicules sont bien couverts dans la littérature, le secteur forestier a beaucoup de caractéristiques uniques qui nécessitent de nouvelles formulations des problèmes et des algorithmes de résolution. À titre d'exemple, les volumes à transporter sont importants comparés à d'autres secteurs et il existe aussi des contraintes de synchronisation à prendre en compte pour planifier l'équipement qui effectue le chargement et le déchargement des véhicules.

Cette thèse traite des problèmes de planification de la chaîne logistique d'approvisionnement en bois: récolter diverses variétés de bois en forêt et les transporter par camion aux usines et aux zones de stockage intermédiaire en respectant la demande pour les différents produits forestiers. Elle propose trois nouvelles formulations de ces problèmes. Ces problèmes sont différents les uns des autres dans des aspects tel que l'horizon de planification et des contraintes industrielles variées. Une autre contribution de cette thèse sont les méthodologies développées pour résoudre ces problèmes dans le but d'obtenir des calendriers d'approvisionnement applicables par l'industrie et qui minimisent les coûts de transport. Cette minimisation est le résultat d'allocations plus intelligentes des points d'approvisionnement aux points de demande, d'une tournée de véhicules qui minimise la distance parcourue à vide et de décisions d'ordonnancement de véhicules qui minimisent les files d'attentes des camions pour le chargement et le déchargement.

Dans le chapitre 3, on considère un modèle de planification tactique de la récolte. Dans ce problème, on détermine la séquence de récolte pour un ensemble de sites forestiers, et on attribue des équipes de récolte à ces sites. La formulation en programme linéaire en nombres entiers (PLNE) de ce problème gère les décisions d'inventaire et alloue les flux de bois à des entrepreneurs de transport routier sur un horizon de planification annuel. La nouveauté de notre approche est d'intégrer les décisions de tournée des véhicules dans la PLNE. Cette méthode profite de la flexibilité du plan de récolte pour satisfaire les horaires des conducteurs

dans le but de conserver une flotte constante de conducteurs permanents et également pour minimiser les coûts de transport. Une heuristique de génération de colonnes est créée pour résoudre ce problème avec un sous-problème qui consiste en un problème du plus court chemin avec capacités (PCCC) avec une solution qui représente une tournée de véhicule.

Dans le chapitre 4, on suppose que le plan de récolte est fixé et on doit déterminer les allocations et les inventaires du modèle tactique précédent, avec aussi des décisions de tournée et d'ordonnancement de véhicules. On synchronise les véhicules avec les chargeuses dans les forêts et dans les usines. Les contraintes de synchronisation rendent le problème plus difficile. L'objectif est de déterminer la taille de la flotte de véhicules dans un modèle tactique et de satisfaire la demande des usines avec un coût minimum. Le PLNE est résolu par une heuristique de génération de colonnes. Le sous-problème consiste en un PCCC avec une solution qui représente une tournée et un horaire quotidien d'un véhicule.

Dans le chapitre 5, on considère un PLNE du problème similaire à celui étudié dans le chapitre 4, mais dans un contexte plus opérationnel: un horizon de planification d'un mois. Contrairement aux horaires quotidiens de véhicules du problème précédent, on doit planifier les conducteurs par semaine pour gérer les situations dans lesquelles le déchargement d'un camion s'effectue le lendemain de la journée où le chargement a eu lieu. Cette situation se présente quand les conducteurs travaillent la nuit ou quand ils travaillent après les heures de fermeture de l'usine et doivent décharger leur camion au début de la journée suivante. Ceci permet aussi une gestion plus directe des exigences des horaires hebdomadaires. Les contraintes de synchronisation entre les véhicules et les chargeuses qui sont présentes dans le PLNE permettent de créer un horaire pour chaque opérateur de chargeuse. Les coûts de transport sont alors minimisés. On résout le problème à l'aide d'une heuristique de génération de colonnes. Le sous-problème consiste en un PCCC avec une solution qui représente une tournée et un horaire hebdomadaire d'un véhicule.

ABSTRACT

The Canadian economy is heavily dependent on the forestry industry; however in recent years, this industry has been adapting to new challenges including a worldwide economic downturn, a strengthening Canadian dollar relative to key competing nations, and a significant decline in newsprint demand. Therefore efficiency in supply chain planning is key for the industry to succeed in the future.

Transportation costs in particular represent a significant expense to forestry companies. This is due to large volumes of product that must be transported over very large distances, especially in the geographic context of a country the size of Canada. While the field of vehicle routing problems has been heavily studied and applied to many industries for decades, the forestry industry has many unique attributes that necessitate new problem formulations and solution methodologies. These include, but are not limited to, very large (significantly higher than vehicle capacity) volumes to be transported and synchronization constraints to schedule the equipment that load and unload the vehicles.

This thesis is set in the wood procurement supply chain of harvesting various assortments of wood in the forest, transporting by truck to mills and intermediate storage locations, while meeting mill demands of the multiple harvested products, and contributes three new problem formulations. These problems differ with respect to planning horizon and varied industrial constraints. Another contribution is the methodologies developed to resolve these problems to yield industrially applicable schedules that minimize vehicle costs: from smarter allocations of supply points to demand points, vehicle routing decisions that optimize the occurrence of backhaul savings, and vehicle scheduling decisions that minimize queues of trucks waiting for loading and unloading equipment.

In Chapter 3, we consider a tactical harvest planning model. In this problem we determine the sequence of the harvest of various forest sites, and assign harvest teams to these sites. The mixed integer linear program (MILP) formulation of this problem makes inventory decisions and allocates wood flow to trucking contractors over the annual planning horizon, subject to demand constraints and trucking capacities. The novel aspect of our approach is to incorporate vehicle routing decisions into our MILP formulation. This takes advantage of the relatively higher flexibility of the harvest plan to ensure driver shifts of desired characteristics, which is important to retain a permanent driver fleet, and also prioritize the creation of backhaul opportunities in the schedule. A branch-and-price heuristic is developed to resolve this problem, with the subproblem being a vehicle routing problem that represents a geographical shift for a vehicle.

In Chapter 4, we assume the harvest plan to be an input, and integrate the allocation and inventory variables of the previous tactical model with vehicle routing and scheduling decisions, synchronizing the vehicles with loaders in the forests and at the mills. The synchronization constraints make a considerably more difficult problem. We use this as a tactical planning model, with no specific driver constraints but a goal of determining vehicle fleet size to maximize their utilization. The objective is to meet mill demands over the planning horizon while minimizing transportation and inventory costs, subject to capacity, wood freshness, fleet balancing, and other industrial constraints. The MILP formulation of the problem is resolved via a column generation algorithm, with the subproblem being a daily vehicle routing and scheduling problem.

In Chapter 5, we consider a similar problem formulation to that studied in Chapter 4, but set in a more operational context over a planning horizon of approximately one month. Unlike the daily vehicle schedules of the previous problem, we must schedule drivers by week to manage situations of picking up a load on one day and delivering on another day, which is necessary when drivers work overnight shifts or when they work later than mill closing hours and must unload their truck on the next day's shift. This also allows for more direct management of weekly schedule requirements. Loader synchronization constraints are present in the model which derives a schedule for each loader operator. Given mill demands, transportation costs are then minimized. We resolve the problem via a branch-and-price heuristic, with a subproblem of a weekly vehicle routing and scheduling problem. We also measure the benefits of applying interior point stabilization to the resource synchronization constraints in order to improve the column generation, a new application of the technique.

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LIST OF ABBREVIATIONS AND ACRONYMS

BPP	Bin Packing Problem
CP	Constraint Programming
CVRP	Capacitated Vehicle Routing Problem
DP	Dynamic Programming
DSS	Decision Support System
ESPPRC	Elementary Shortest Path Problem with Resource Constraints
FIFO	First In First Out
GRASP	Greedy Randomized Adaptive Search Procedure
HVRP	Heterogeneous Vehicle Routing Problem
IPS	Interior Point Stabilization
IRP	Inventory Routing Problem
IRPPD	Inventory Routing Problem with Pickups and Deliveries
LP	Linear Program
LTSP	Log Truck Scheduling Problem
MDVRP	Multi-Depot Vehicle Routing Problem
MILP	Mixed Integer Linear Program
OR	Operations Research
PDP	Pickup and Delivery Problem
PRP	Production Routing Problem
SDVRP	Split Delivery Vehicle Routing Problem
SLTSP	Synchronized Log Truck Scheduling Problem
SPPRC	Shortest Path Problem with Resource Constraints
TSP	Traveling Salesman Problem
VRP	Vehicle Routing Problem
VRPMS	Vehicle Routing Problem with Multiple Synchronization Constraints
VRPPD	Vehicle Routing Problem with Pickups and Deliveries
VRPTT	Vehicle Routing Problem with Trailers and Transshipments
VRPTW	Vehicle Routing Problem with Time Windows

$\mathcal{NP}$	Non-Deterministic Polynomial Time
$\mathbb{R}$	Set of Real Numbers
$\mathbb{R}_{\geq 0}$	Set of Non-Negative Real Numbers
$\mathbb{Z}$	Set of Integers
$\mathbb{Z}_{\geq 0}$	Set of Non-Negative Integers
$\mathbb{1}(\bullet)$	Binary Indicator Function on Conditional Statement $\bullet$

CHAPTER 1

INTRODUCTION

1.1 Preliminaries

Canada is a country rich in natural resources, and our economy is reliant on resource-based industries such as fisheries, forestry, agriculture and mining. With approximately 400 million hectares of forest and other wooded land, the forestry industry in particular plays a large role; in 2012 it contributed 19 billion dollars to national GDP and directly created 235,900 jobs (Natural Resources Canada).

In recent years, the forestry industry has been adapting to new challenges including a worldwide economic downturn, a strengthening Canadian dollar relative to key competing nations, and a significant decline in newsprint demand. Therefore innovation in products and processes is vital to long term competitiveness. Within this industry, supply chain planning has received much focus in recent years; forest product supply chains create massive networks over which the wood fiber flows and is transformed into consumer products. This has necessitated the development of many operations research (OR) methodologies and decision support systems (DSSs) to resolve these problems, reducing costs and environmental footprint at every step.

We consider the wood procurement supply chain, in which wood is harvested in the forest and transported (usually by truck) to mills and intermediate storage locations. The wood is produced and delivered subject to demands of timber of many different characteristics such as species, length, diameter, quality, and freshness. The volumes of timber that must be transported are very large: in 2011, harvested volumes of roundwood in Canada cumulated 146.7 million cubic meters (Canadian Council of Forest Ministers). These volumes must be transported over very large distances, especially in a country with the geographical attributes of Canada. Therefore transportation costs represent a massive expense to the Canadian forest sector, and this thesis is focused on primarily reducing these costs.

The problem definitions in this supply chain differ by planning horizon. The forestry industry planning hierarchy is typically decomposed into strategic, tactical, and operational problems. In this thesis, we consider tactical planning (in which wood flow and inventory decisions are typically linked with harvest scheduling) and the operational planning (in which detailed driver and loader schedules are created). In the latter case, this is commonly referred to as a log-truck scheduling problem (LTSP).

This necessitates the integration of production and inventory planning, vehicle routing and scheduling, and loader scheduling. For clarification, vehicle routing refers to the order of pickups and deliveries each vehicle makes to form a geographical route, whereas vehicle scheduling determines the exact time of each of these pickups and deliveries. The vehicle and loader scheduling in particular provide a challenge specific to the forest products sector. While the field of vehicle routing problems (VRPs) has seen much focus from an OR perspective for many decades, the literature on problems that include synchronization constraints between vehicles and other equipment (in this case a crane that loads and unloads the trucks) has been much more sparse. The existence of these constraints creates much more difficult problems to solve; hence providing tight optimality gaps on problems of practical size is not possible, and rather the goal is to provide quality solutions to industry decision makers in a reasonable time frame.

Through collaboration with these decision makers, three problem formulations were developed to manage transportation planning with different goals and side constraints that vary based on planning horizon and the objectives and practices of the companies. In the following chapters, we detail the problem definitions, mixed integer linear program (MILP) formulations, solution methodologies, and results and savings obtained.

1.1.1 FPInnovations

FPInnovations is a private, non-profit forest research centre that was created in 2007 through a merger of Forintek Canada Corporation, the Forest Engineering Reearch Institute of Canada (FERIC), the Pulp and Paper Research Institute of Canada (Paprican), and the Canadian Wood Fibre Centre. Its mission is to facilitate ongoing forest sector renewal through the development of scientific and technical solutions, through collaboration with members in the private sector and partners in academia and government.

The Value Maximization and Decision Support (VMDS) research group of FPInnovations helps member companies generate more value by implementing value chain concepts and developing decision support tools driven by market needs. It is through collaboration with this group that the direction of this thesis has been guided, developing DSSs for use with member companies based on their varying needs and constraints.

1.2 Organization of the Thesis

In Chapter 2, we provide a comprehensive literature review. We survey VRP and inventory routing problem (IRP) literature, covering formulations that share attributes with the problems studied in this thesis. We follow this with a review of column generation and branch-and-price procedures in vehicle routing problems, illustrated with an application to a capacitated vehicle routing problem (CVRP). Finally, we survey OR in the forest products industry, based in the context of the wood supply chain of harvesting, inventory management, and transportation.

Chapters 3 through 5 form the body of this thesis: the three articles that have been produced over the course of these doctoral studies. Chapter 3 presents *A Transportation-Driven Approach to Annual Harvest Planning*, which has been submitted for publication to the special issue *Advances in Transportation and Logistics* of *Transportation Research Part C: Emerging Technologies*. Chapter 4 presents *A Column Generation Algorithm for Tactical Timber Transportation Planning*, which has been accepted for publication in the *Journal of the Operational Research Society* (Rix et al., 2015). Chapter 5 presents *Dock and Driver Scheduling in a Timber Transport Supply Chain*, which has been submitted for publication to *Computers & Operations Research*. Finally, Chapter 6 provides a general discussion and Chapter 7 concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

In this chapter we provide an extensive literature review. First, we give a survey of VRPs and solution approaches that share attributes with the problems that we examine in this thesis. Following this, we examine the current state of transportation-based methodologies and DSSs that have been developed for use in the forest products sector.

2.1 Related Vehicle Routing Problems

In this section we survey closely related problems to the ones encountered in this thesis. We then give a more detailed summary of column generation techniques in this field. For illustrative purposes, we outline a branch-and-price procedure on the CVRP, which will introduce modeling and methodological techniques used in this thesis.

2.1.1 Vehicle Routing Problems

VRPs arise as important problems with many industrial applications in transportation, distribution, and logistics. In the VRP, the goal is to serve a set of client locations, each exactly once, with a fleet of vehicles delivering a commodity. Each vehicle route originates and terminates at a depot location, and the objective is to minimize total traveling cost. The VRP is known to be $\mathcal{NP}$-hard as even its simplest form, the traveling salesman problem (TSP) with a single vehicle, is $\mathcal{NP}$-hard (Garey and Johnson, 1979).

VRPs that arise in practice are usually defined under route length and vehicle capacity restrictions. In the case of a homogeneous vehicle fleet, each of which has a limited capacity of the commodity being delivered to the clients, this is commonly referred to as the CVRP. This problem was first formally introduced by Dantzig and Ramser (1959), who gave a MILP representation of the problem. Literature on the VRP and CVRP is vast in both exact and heuristic methods; for more detailed surveys we direct the reader to Toth and Vigo (2001) and Laporte (2009).

Heuristic methods fall into several classes. We first mention constructive, or one-phase, heuristics that build a solution by iteratively expanding a partial solution. One classic one-phase heuristic for the CVRP was proposed by Clarke and Wright (1964). This savings heuristic ranks client pairs according to the realized savings from visiting the customers consecutively rather than in separate routes. This ranking is then used to modify a solution by merging routes in order to maximize the incidence of these client pairs. Two-phase heuristics decompose the problem into two distinct subproblems; cluster-first route-second decompositions are the most common (Bramel and Simchi-Levi, 1995).

One and two-phase heuristics tend to converge to a local optimum and hence may not reach the global optimum. For this reason, the use of metaheuristics that allow for deterioration of the objective function during exploration of the solution space is commonplace. Gendreau et al. (1994) developed TABUROUTE to resolve the CVRP; this uses the tabu search heuristic (Glover and Laguna, 1999) in which a tabu list is maintained in order to prevent cycling. Pisinger and Ropke (2007) present an adaptive large neighborhood search heuristic, using a set of destroy and repair methods to explore the solution space while simultaneously tracking the performance of each method in order to best guide the search. Cordeau et al. (2005) provide a computational comparison of many of the more popular CVRP heuristics.

Many exact methods for the CVRP are based on the formulation of Dantzig and Ramser (1959). Valid inequalities and separation algorithms have been proposed by several authors (Letchford et al., 2002; Lysgaard et al., 2004) and integrated into branch-and-cut algorithms. However these branch-and-cut methods do not scale well to larger problem instances. Many authors have opted to use branch-and-price approaches that take advantage of a stronger set partitioning formulation, first derived by Balinski and Quandt (1964), though it comes at the expense of an exponential number of variables. Fukasawa et al. (2006) and Baldacci et al. (2008) provide branch-and-cut-and-price procedures that take advantage of both methods.

There are many variations of the VRP and CVRP, with a wide array of formulations and constraints that can be added in nearly any combination; we identify several of the most common that can be considered. A natural extension of the VRP is the multi-depot vehicle routing problem (MDVRP), in which vehicles are routed from a set of facilities rather than solely one. With each facility is associated a capacity representing the maximum amount of commodity that can be served from the facility, and both vehicle and facility capacities must be respected in a solution. In general, this problem is much more difficult than the VRP. Baldacci and Mingozzi (2009) presented a unified framework for modeling and solving several classes of vehicle routing problems, including the MDVRP. The authors provide a set-partitioning formulation of the MDVRP, and solve it via branch-and-cut-and-price. Cordeau et al. (1997) solved the MDVRP with a tabu search heuristic.

Heterogeneous vehicle fleets are common in many industries, in which vehicles can have various capacities, fixed costs, and variable costs. Golden et al. (1984) first introduced the heterogeneous vehicle routing problem (HVRP), and most work since has been based on heuristic methods, such as the tabu search method of Gendreau et al. (1999). Choi and Tcha

(2007) solved this problem with column generation using several dynamic programming (DP) schemes for the subproblem, and on termination of the column generation found an integer feasible solution by solving a MILP.

In the vehicle routing problem with time windows (VRPTW), an additional constraint is imposed representing that each client must be visited during a specific time interval. A vehicle can wait in the case of early arrival, but late arrival is forbidden. This problem is very well studied in the literature, and Baldacci et al. (2012) provide a recent survey on exact methods. The most effective methods are based on branch-and-price, first implemented on this problem by Desrochers et al. (1992). Many heuristic methods have also been studied, including tabu search (Cordeau et al., 2001) and a branch-and-price based large neighborhood search (Prescott-Gagnon et al., 2009). Kontoravdis and Bard (1995) implemented a greedy randomized adaptive search procedure (GRASP) procedure, in which a simple deterministic greedy algorithm has randomization added in order to diversify the search.

In most VRPs, the assumption is that demand of each client is less than or equal to the capacity of a single vehicle. In many contexts, this is not the case and when it is necessary to visit a client more than once, we must relax this single visit requirement. Dror and Trudeau (1990) defined the split delivery vehicle routing problem (SDVRP), proposed a local search heuristic, and showed how the savings resulting from an SDVRP formulation compared to a VRP formulation grow significantly as client demand size grows relative to vehicle capacity. An MILP formulation is given by by Dror et al. (1994). Ho and Haugland (2004) propose an effective tabu search heuristic for the time window variant of the SDVRP.

One very well-studied class of VRP is the pickup and delivery problem (PDP), in which objects or people have to be transported between origins and destinations. Berbeglia et al. (2007) survey the PDP and provide a classification scheme. The authors distinguish between three structures of PDP based upon the number of origins and destinations of the commodoties: one-to-many-to-one, many-to-many, and one-to-one. In one-to-many-to-one problems, commodoties are delivered from the depot to the clients and/or from the clients to the depot. In the many-to-many problems, any location can be a source or destination for any commodity. In one-to-one problems, each commodity has a fixed origin and fixed destination. One-to-one problems are sometimes referred to as vehicle routing problems with pickups and deliveries (VRPPDs), and have many applications such as door-to-door transportation services (Cordeau and Laporte, 2007).

Ropke et al. (2007) formulated the time window variant of the VRPPD, and resolved it via branch-and-cut. Xu et al. (2003) also considered a time window variant of the VRPPD with a heterogeneous vehicle fleet, defining multiple time windows for each pickup and delivery point. A set partitioning formulation was proposed and hence a column generation algorithm was used to resolve the problem. Many heuristics have also been used on this problem: Bent and Van Hentenryck (2006) gave a two stage heuristic in which simulated annealing is used to reduce the number of vehicles, following which large neighborhood search is used to minimize travel costs.

2.1.2 Inventory Routing Problems

When vehicle routing decisions must be solved concurrently with inventory decisions at client locations, usually in the context of vendor managed inventory resupply policies, we refer to this VRP extension as the IRP. This is very different from the VRP as the supplier is the one responsible for satisfying the client orders, operating under the constraint that clients do not run out of product. Moreover, it is modeled over a multi-period time horizon, with inventory managed between periods. Bell et al. (1983) gave a first application of this problem in the management of industrial gases.

Coelho et al. (2013) give a recent survey and classify the current IRP literature according to a number of criteria, a few of which we will discuss. While the majority of IRPs considered in literature deal with a homogeneous vehicle fleet, or in many cases a single vehicle, heterogeneous vehicle fleets have been considered. Additionally, IRPs typically operate under one of two inventory policies. Under a maximum level policy, replenishment level is flexibile but must satisfy upper and lower bounds. On the other hand, an order-up-to policy is one in which immediate replenishment up to the upper bound is required when the level falls to the predetermined lower bound. In both cases, it is possible to allow for stockout (negative inventory) at penalty.

Coelho and Laporte (2012) formulated the IRP, and gave a branch-and-cut procedure for its resolution. Exact methods such as this can generally solve within reasonable time instances up to 25 customers, 3 periods, and 3 vehicles; beyond which gap sizes are rather large. Desaulniers et al. (2014) gave a branch-and-price-and-cut methodology that was able to solve to optimality additional benchmark instances.

Coelho et al. (2013) further classify three basic problem structures: one-to-one, one-to-many, and many-to-many. The many-to-many IRP is a less-studied variant; Ramkumar et al. (2012) considered a many-to-many problem involving multiple commodities and give a MILP formulation. A column generation based approach was also been successfully applied to a many-to-many IRP in maritime logistics (Christiansen and Nygreen, 2005).

Michel and Vanderbeck (2012) consider a two-phase approach. In a tactical planning phase, they minimize a rough measure of routing cost by assigning clients to vehicles, while the routing is saved for an operational planning phase. A branch-and-price-and-cut heuristic is used to resolve the problem. Van Anholt et al. (2013) introduced the inventory routing problem with pickups and deliveries (IRPPD) in the context of replenishment of automated teller machines, and used a branch-and-cut algorithm to resolve the problem. The IRPPD combines the features of the IRP and the PDP.

It is natural to think that integrating further elements of the supply chain can lead to even better performance, and Chandra and Fisher (1994) were among the first to include production decisions within the IRP, producing operating cost reductions from 3 to 20%. This problem is classified as the production routing problem (PRP). Adulyasak et al. (2013) gave strong formulations of this problem in the multi-vehicle context, and solved with an adaptive large neighborhood search heuristic to find initial solutions, followed by a branch-and-cut procedure. Other recent methodological focuses in this field have included tabu search (Bard and Nananukul, 2009) and branch-and-price (Bard and Nananukul, 2010).

2.1.3 Synchronization in Vehicle Routing

In most variants of the VRP, including the ones referenced thus far in this chapter, vehicles are mutually independent. That is, a change in one vehicle route does not affect any other vehicle route; however in many contexts this is not the case. A classic example is the vehicle routing problem with trailers and transshipments (VRPTT) (Drexl, 2013), in which non-autonomous vehicles (trailers) can move only when accompanied by other vehicles. Bredström and Rönnqvist (2008) formulate a VRP with temporal precedence and synchronization constraints, with applications in several fields including homecare staff scheduling (two nurses must visit patients at the same time for lifting purposes or with fixed offset to give medicine after a meal) and airline scheduling (a coded flight must depart at the same time each day). Salazar-Aguilar et al. (2012) present a synchronized arc routing problem for snow plowing operations, in which vehicle routes are designed so that street segments with multiple lanes of the same orientation are plowed simultaneously by multiple vehicles.

Drexl (2012) provides a survey and classification scheme for the vehicle routing problem with multiple synchronization constraints (VRPMS), and distinguish between several types of synchronization. We primarily focus on resource synchronization: defined by the authors as

> At any point in time, the total utilization or consumption of a specified resource between all vehicles must be less than or equal to a specified limit.

The inclusion of resource synchronization constraints in vehicle routing is a relatively new field of research, and the literature to date very sparse. Hempsch and Irnich (2008) introduced resource synchronization (under the definition “intertour resource constraints”) in order to model a restricted number of docking stations at a destination depot. They gave a local search heuristic to solve the problem. Ebben et al. (2005) gave an application in an automated transport system for automated guided vehicles at an airport. The resources in the formulation are vehicles, docks for (un)loading, parking spots, and cargo storage. Discrete event simulation was used in the problem resolution.

2.1.4 Branch-and-Price for Vehicle Routing Problems

In this section we provide in further detail a branch-and-price procedure that can be applied to the problems described thus far in this literature review. Column generation is an efficient algorithm for solving large linear problems; that is, linear programs whose variable sets are too large to practically construct and store. When a column generation procedure is embedded into a branch-and-bound search tree, this is referred to as branch-and-price (Barnhart et al., 1998). Branch-and-price is a widely used technique in classic problems such as vehicle routing, crew scheduling, and facility location. Desaulniers et al. (2005) give a detailed description and walk through a number of applications.

Mathematical Formulations for the Capacitated Vehicle Routing Problem

As a compact example, consider again the CVRP. We give an explicit definition on an undirected graph $G = (V, E)$, where $V = \{0, 1, \ldots, n\}$ is a set of $n + 1$ vertices. Vertex 0 defines the depot and the remaining vertices represent n clients. Let q_i be the demand of each client i ($q_0 = 0$). A set of m homogeneous vehicles of capacity Q is based at the depot. Each edge e is associated with a cost c_e of traversal.

To formulate the CVRP as a MILP, we use the formulation of Laporte et al. (1985), in which decision variables x_e define the number of times edge e is traversed in a solution. Additionally, we define $\delta(S)$ to be the cutset of subset $S \subseteq V$, that is, $\delta(S) = \{(i, j) \in E : i \in S, j \notin S\}$. We denote by (VF) the two-index vehicle flow formulation below.

$$\text{(VF)} \qquad \min \sum_{e \in E} c_e x_e \tag{2.1}$$

subject to

$$\sum_{e \in \delta(\{i\})} x_e = 2, \qquad \forall i \in V \backslash \{0\}, \tag{2.2}$$

$$\sum_{e \in \delta(\{S\})} x_e \geq 2k(S), \qquad \forall S \subseteq V \backslash \{0\}, |S| \geq 2, \tag{2.3}$$

$$\sum_{e \in \delta(\{0\})} x_e = 2m, \tag{2.4}$$

$$x_e \in \{0, 1, 2\}, \forall e \in \delta(\{0\}), \tag{2.5}$$

$$x_e \in \{0, 1\}, \forall e \in E \backslash \delta(\{0\}), \tag{2.6}$$

where $k(S) = \lceil \frac{\sum_{i \in S} q(S)}{Q} \rceil$, though this bound can potentially be tightened by solving a bin packing problem (BPP), which is $\mathcal{NP}$-hard. The objective function (2.1) is the minimization of total cost. Constraints (2.2) are degree constraints forcing each client to be visited exactly once. Constraints (2.3) are capacity and subtour elimination constraints which impose at least $k(S)$ vehicles must enter and leave S. Constraints (2.4) fix the number of vehicles to m, and constraints (2.5) and (2.6) are integrality constraints. As a clarification, $x_e = 2$ if and only if a vehicle route serves only a single client before returning to the depot.

Balinski and Quandt (1964) were the first to propose a set partitioning formulation for the CVRP. Let R denote the set of all feasible vehicle routes. Each route is associated with a cost c_r, and we define the binary matrix $A = (a_{ir})$ where $a_{ir} = 1$ if and only if client i is visited in route r. We then let y_r be a boolean variable specifying whether or not route r is selected in the solution. The set partitioning formulation is defined below, and we denote it (SP).

$$\text{(SP)} \qquad \min \sum_{r \in R} c_r y_r \tag{2.7}$$

subject to

$$\sum_{r \in R} a_{ir} y_r = 1, \qquad \forall i \in V \backslash \{0\}, \tag{2.8}$$

$$\sum_{r \in R} y_r = m, \tag{2.9}$$

$$y_r \in \{0, 1\}, \forall r \in R. \tag{2.10}$$

The objective function (2.7) is again the minimization of total cost. Constraints (2.8) force each customer to be visited exactly once, and constraints (2.9) require m vehicles to be used. Constraints (2.10) are integrality constraints.

Applying Column Generation to the Linear Relaxation

The motivation for using branch-and-price to solve the CVRP is that the linear relaxation of the two-index vehicle flow formulation (VF) is very weak relative to that of formulation (SP) (Bramel and Simchi-Levi, 1997). Specifically, any solution y to the linear relaxation of (SP) can be transformed into a relaxed solution x to (VF), but the converse is not true. Hence using formulation (SP) is preferable; however, as the size of the variable set R grows exponentially with the problem size, it is impractical to construct and store. A column generation procedure will start with a partial set R' that will be enriched iteratively by solving a subproblem. We refer to the relaxation of (SP) as the master problem.

To enrich R' it is necessary to uncover new routes that offer a better way to visit the clients. This is the case if the new route has a negative reduced cost. The reduced cost of a route is calculated by replacing the cost of each edge c_{ij} with its reduced cost $\hat{c}_{ij} = c_{ij} - \lambda_i$, where λ_i is the dual value associated with the constraint (2.8) for client i. Hence a negative reduced cost route is a route in which the sum of the dual values is more than the costs of the traveled edges. If no routes outside of R' with a negative reduced cost exist, then it suffices to solve the linear program with only the pool R' to yield an optimal solution. A column generation procedure will therefore iterate between solving the master problem and subproblem until no more negative reduced cost routes remain; at this point the master problem can be solved to optimality.

Solving the Subproblem

To find a negative reduced cost route to add to the set partitioning formulation above, one can solve an elementary shortest path problem with resource constraints (ESPPRC). That is, one must find an elementary (cycle-free) path from the depot to the depot that both satisfies capacity constraints and has a negative reduced cost. As arc costs (and thus cycle costs) can be negative, elementarity is not trivially fulfilled in this case. This makes the subproblem $\mathcal{NP}$-hard. However, effective techniques have been generated to solve this problem. Feillet et al. (2004) show how this can be solved exactly with DP using a label correcting algorithm. However, this problem is usually solved heuristically; for example Desaulniers et al. (2008) introduced a tabu search heuristic. Another interesting heuristic is to instead solve a 2-cyc-SPPRC, in which only cycles of length 2 are forbidden. This problem can be solved in pseudo-polynomial time.

As we will see in later chapters, the formulations studied in this thesis do not have elementarity restrictions. Therefore it suffices to solve an SPPRC, in which polynomial time label correcting algorithms can be used under certain conditons (Cormen et al., 1990).

Stability Problems

Any column generation procedure is heavily dependent on the marginal costs (dual values) to guide the search of the subproblem. However, these values may be poorly estimated, especially early in the search. Neame (1999) provides a detailed discussion on this topic.

A first stabilization approach is to move from a set partitioning (SP) to a set covering formulation. This is more effective because in a set partitioning formulation, it is possible to have negative dual values associated with the partitioning constraints (2.8), which is problematic as visiting a client can have negative value in the subproblem. Therefore the equality in the constraint is replaced with a non-strict greater-than inequality; we define this new problem (SC).

However, dual values can still be poorly estimated due to the relaxation of (SC) being degenerate; hence the dual problem has an infinite number of optimal solutions. If an extreme point of the dual polyhedron is returned, as is common when retrieving dual values in most linear program (LP) solvers, this will yield very large dual values for some constraints and values of zero for others; in a CVRP setting this means very high benefit for visitng some clients and no benefit for others. A better approach would be to take a dual solution from the interior of the dual polyhedron. Bixby et al. (1992) give an interior point method for solving LPs; unfortunately iterations are slower than using a simplex based method and as interior point methods can not be warm started, they do not take advantage of the iterative procedure of column generation.

Other stabilization approaches have been widely used, such as the box-pen method proposed by Du Merle et al. (1999). Interior point stabilization (IPS) (Rousseau et al., 2007) is another technique, in which the LP is solved multiple times with minor modifications in order to retrieve multiple extreme dual solutions, of which a convex combination is then taken.

Branching Scheme

Upon solving the linear relaxation of the set covering formulation (SC) to optimality with column generation, if the resulting solution is integer feasible, it will be the optimal solution to the MILP. However, this is unlikely to be the case and therefore the column generation procedure must be implemented into a branch-and-bound tree in order to solve the MILP exactly.

While the most intuitive branching decisions would be on the variables y_r, this is problematic for a number of reasons. First, this significantly modifies the subproblem. While imposing $y_r = 1$ is easy (the visited clients are removed from the problem), imposing $y_r = 0$ poses much more difficulty, and this necessitates that the subproblem find 2 negative reduced cost routes to add to the master to guarantee the existence of a new route. This will continue to increase by 1 every time a route is forbidden, which can be very inefficient. Second, this type of branching creates an imbalanced search tree: $y_r = 1$ is very strong but $y_r = 0$ has a very minimal impact on the size of the feasible space.

A more common approach is to instead branch on the variables of the formulation (VF). That is, an edge $e = (i, j)$ is chosen such that the summation of all variables y_r representing routes r that traverse that edge is fractional. This summation (which is equivalent to variable x_e) is then branched on. These restrictions are easily added to the subproblem by removing the appropriate edges to either restrict or force traversal of edge e in the solution.

Resolving a problem through an exact branch-and-price method can be very time consuming, and is only practical on small problem instances. Often, branch-and-price methodologies are used heuristically in order to generate quality solutions under a reasonable time limit. For example, Choi and Tcha (2007) could only solve HVRP cases with up to 20 clients exactly; hence they used the basic heuristic of solving the LP relaxation to optimality, restoring integrality to the necessary variables, and solving the resulting MILP with branch-and-bound and the restricted set of columns generated to that point. This same heuristic was used by Xu et al. (2003) on their PDP with multiple time windows. We also mention the large neighborhood search based branch-and-price algorithm of Prescott-Gagnon et al. (2009) applied to the vehicle routing problem with time windows. In this case, the route variables y_r are branched on, but they are only fixed to value 1 with no backtracking.

2.2 Operations Research in the Forest Products Industry

Within the forest products industry, D'Amours et al. (2008) present an overview of different supply chain planning problems and review the contributions in an OR setting. The product flow of the supply chain is shown in Figure 2.1. The authors distinguish between the strategic, tactical, and operational planning levels. Supply chain planning in this industry is especially difficult, with a hierarchy that can be difficult to classify, since planning horizons can range from well over 100 years to seconds. As a general rule, strategic planning is defined as problems with time horizons greater than 5 years, tactical problems have horizons between 6 months and 5 years, and operational problems have horizons of less than 6 months. These definitions, of course, vary between companies and their decision makers.

While operational problems such as board cutting and truck dispatching must be solved in minutes or even seconds, strategic and tactical problems can be solved over a period of up to several hours (Rönnqvist, 2003). For this reason, while heuristics, meta-heuristics and network methods are generally used in operations planning, mixed integer linear programming

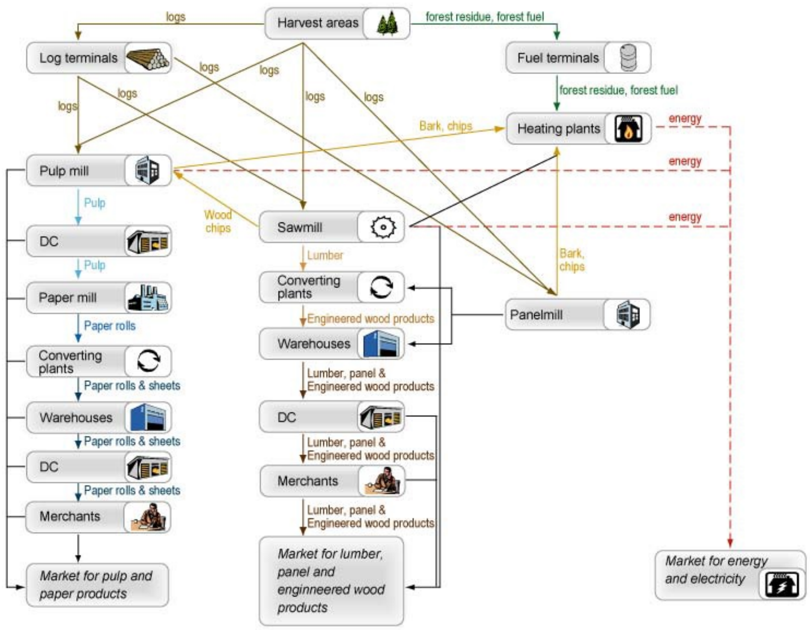

Figure 2.1 The different supply chains of the forest products industry (D'Amours et al., 2008, Figure 1)

and stochastic programming based methods are often used to solve tactical and strategic problems.

Forest product supply chains create massive networks over which the wood fiber flows and is transformed into consumer products. These transformations are many-to-many processes, which take a set of input products and produce a set of output products, and many times decisions must be made on the transformation to use. These decisions can range from a recipe at a pulp and paper mill to a cutting pattern to use on a harvested tree in the forest.

This thesis is set in the context of the wood procurement supply chain, starting in the forest. First, a harvest team will cut the trees, remove the branches, and buck the tree into logs classified by species, length, diameter and quality. These are then transported, usually by truck but train and barge are also used, to mills or to intermediate storage locations. A log loader with operator must usually be present to load and unload trucks, though some trucks are equipped with their own cranes and most mills have permanent equipment on site. The transport companies that deliver these harvested logs may also use their trucks and drivers to deliver other products in the supply chain; for example multi-product trailers can additionally be used to haul wood chips from a sawmill to a pulp and paper mill.

We present in the rest of this section the types of problems encountered in wood procurement planning, and the OR methodologies that have been implemented to solve these problems. We will also focus on DSS implementations of these methodologies that have been developed for industrial use.

2.2.1 Harvest Scheduling

Tactical models in forest management are commonly used to decide where and when to harvest, which team to use in each harvest decision made, and where and when to transport and store the harvested timber. These plans are made up to 5 years in advance, but are often re-evaluated annually when doing budget projections for the following year. Rönnqvist (2003) gives a simple MILP model incorporating these decisions in which the objective function measures two costs: the cost of harvesting a forest area by a team in a specific period, and the cost of delivering each unit of wood from a forest site to a mill. Epstein et al. (2007a) and Gémieux (2009) give recent surveys on OR applications to harvest operations.

Beaudoin et al. (2007) derive an MILP to support the tactical wood-procurement decisions of a multi-facility company. This formulation considers wood freshness and quality with respect to the age of harvested wood. The objective is to maximize company profits, with market prices appearing as a function of supply volume, freshness and market conditions. The authors utilize a multi-criteria decision making process which achieves an average profitability increase of 8.8% relative to solving a deterministic model using average parameter values.

Karlsson et al. (2004) consider an annual harvest planning problem that arises in Sweden, in which inventory management and road openings and closings must be managed. To solve the MILP model, they use a variable fixing heuristic in which they iteratively solve LP relaxations, at each iteration fixing binary variables with a fractional value in chronological order until a feasible solution is found.

Bredström et al. (2010) consider a tactical problem in which machines must be scheduled to plan the harvest, and also include the minimization of their movement in the objective function. They do not, however, include transportation or inventory costs of the timber. They use a two-phase approach in which they first assign machines to forest locations, and then schedule each machine to minimize their moving costs.

In the tactical model of Bajgiran et al. (2014), the harvesting and procurement are scheduled in tandem with production, distribution and sales decisions, with an objective of maximizing total profit. They do not schedule harvest teams or equipment, but instead sequence the harvest of available forest areas. They formulate an MILP and develop a Lagrangian relaxation based heuristic with which to resolve the problem.

Similar models appear in planning over a shorter time horizon, including more operational details to increase efficiency. Karlsson et al. (2003) consider a harvest planning model over a period of 4 to 6 weeks, in which harvest teams are scheduled, transportation and inventory are managed, and additionally the management and maintenance of roads must be considered to yield a feasible solution.

Mitchell (2004) gives a very detailed description of operational harvest scheduling in the Australian and New Zealand context. Road maintenance and management are not considered in this model; however a key term of their objective is to maximize profitability by incorporating the revenue associated with each potential log type produced. They use a branch-and-price scheme by pricing variables that represent harvest crew schedules via DP.

Epstein et al. (1999) present OPTICORT, created for use in the Chilean forest sector. They additionally include machine assignment and bucking decisions in a short term (3 months) harvesting model. OPTICORT uses a MILP model, solved by column generation.

Gerasimov et al. (2013) integrate harvesting and transportation decisions into a single DSS for use in the Russian forestry sector. On an extensive transportation network, improving paths are generated heuristically and used to influence the routing of both harvest teams and trucks, solved via a DP algorithm. Potential cost savings of 14 to 25% were reported.

2.2.2 Transportation

At the tactical level of wood procurement planning, little emphasis is placed on transportation. Along with the upgrade of transportation infrastructures and adjustment of transportation equipment capacity, volume allocations from supply points to demand points are often decided. When formulating annual plans, the total cost of wood flow from forest sites to mills is minimized based on out-and-back travel distance, with more detailed transportation plans determined at the operational level. As detailed in the previous section, they are typically incorporated in harvest planning models (Rönnqvist, 2003).

At the operational level, more detailed transportation plans are determined in which vehicle routes are constructed under the objective of minimizing transportation costs. When necessary, synchronization with loaders at supply and demand points are scheduled and queuing times are minimized. In the forestry industry, the problem of creating these plans is commonly called the LTSP.

The LTSP is a generalization of the aforementioned PDP or, in a multi-period planning context in which inventory must be managed at the daily or weekly level, the IRPPD. The underlying structure is often that of a many-to-many PDP, in the case where any supply vertex can satisfy any demand of the given product. Thus geographic allocation decisions must be decided in the planning. However in many contexts, and often the case in Canada, there are contractual obligations arising from timber auctions in which the pairings of supply to demand are fixed. Hence this defines a PDP of a one-to-one structure. A common solution procedure for many-to-many problems is to decompose the problem in two phases: the first solves the allocation and derives a one-to-one PDP; the second solves the resulting PDP.

The LTSP also differs from more classic PDP applications that arise in the literature based on several key criteria. First, harvest volumes of timber usually are much larger than in other industries: much larger than the volume of a single truck. This necessitates many trips to the same client vertices, as in an SDVRP. Second, forestry companies generally do not employ a single homogeneous fleet of trucks. In fact, approximately 80% of the timber trucks in Canada belong to independent owner-operators (Audy et al., 2013). This leads to a very fragmented heterogeneity in the truck fleet: differing in terms of fixed and variable costs, capacity of each product, locations of the facility at which to start and end routes, driver shift lengths and potentially priorities, allowable operating areas, and the availability of an onboard loader. Hence these problems share attributes with the HVRP and MDVRP. Third, working hours for the loader operators at forest sites and mills explicity define time windows, as in a VRPTW, though these windows are generally not as tight as in other industries and some mills are in fact operating 24 hours per day. When planning over a horizon of greater than one day, multiple time windows can arise to account for daily changes in operating hours. Finally, synchronization between loaders and trucks is necessary in nearly all contexts (though trucks equipped with onboard loaders can arise as an exception), and hence the LTSP generalizes the VRPMS.

There is much literature devoted specifically to the LTSP, and for recent surveys we direct the reader to Epstein et al. (2007b) and Audy et al. (2012). We emphasize that throughout the literature, the exact problem definition changes with respect to the setting of the problem and the industrial objectives and constraints to be imposed. Heuristic methods and MILP techniques have both been applied to this problem, though we note that due to the complexity of the problem, solving it exactly in an MILP setting is not feasible for problems of a practical size.

The savings heuristic of Clarke and Wright (1964) was applied to the transportation in the forest sector by Gingras et al. (2007). Based on the volumes of products at supply points and their destinations, and the compatibility of truck configurations with the products, potential backhaul tours are generated and ranked according to their savings. This heuristic has been included in the control platform module FPInterface, under the name MaxTour. We note that this does not solve a full LTSP by assigning routes and schedules to trucks; however its solution has been used by industry decision makers to assist in manual routing and dispatching.

FlowOpt is a similar DSS to MaxTour, developed by the Forestry Research Institute of Sweden (Forsberg et al., 2005). It allocates volume from supply points to demand points via an LP solver, integrating transport from truck, train, and ship, calculating the savings of backhaul tours. Frisk et al. (2010) describe an implementation with up to 8 companies in order to yield transportation savings through lumber exchanges, with savings of up to 12.8%.

Beck and Sessions (2013) developed an ant colony optimization heuristic to solve a similar problem in wood chip transportation. They also used a flow-based formulation of the problem, with the additional constraint of adding fixed costs to road segments that must be cumulated to account for modifications that give each truck configuration access to the forest transportation network. Ant colony optimization (Dorigo et al., 2006) is based on the analogy of ants searching for food: ants leave behind a pheromone scent that influence other ants to take the path, and as more ants travel over the same path the scent increases.

Due to the success of the tabu search algorithm of Cordeau et al. (2001) on the VRPTW, it has been applied to LTSPs. In a one-to-one structure, Gronalt and Hirsch (2007) developed a regret heuristic to find an initial solution and then used tabu search to find improving solutions. Flisberg et al. (2009) operated in the context of a many-to-many structure, and solved the problem in 3 phases. First, an LP determined wood flows between supply and demand vertices, and then an MILP created full truckloads from these flows. Finally, an initial solution to the LTSP is generated heuristically and tabu search is applied to improve the solution. Rummukainen et al. (2009) used a similar problem decomposition, using tabu search to first create truckloads, then a MILP model to allocate truckloads from supply vertices to demand vertices. In the final phase, tabu search is again used to route the trucks.

The methodology of Flisberg et al. (2009) has been included as the optimization procedure in the DSS RuttOpt (Andersson et al., 2008), designed by the Forestry Research Institute of Sweden, which was tested on case studies with up to 110 trucks and 3800 transport requests over 5 days. It is currently used to measure routing efficiency in an association of Swedish carriers, and to identify backhaul opportunities that arise from load exchanges between the carriers (Audy et al., 2012).

Moura and Scaraficci (2008) proposed a hybrid approach using GRASP and LP methods to solve a one-to-one LTSP with a homogeneous vehicle fleet. Simulated annealing is another commonly used heuristic for optimization problems, and was applied to the LTSP by McDonald et al. (2010). This method iteratively applies modifications to the current solution, and chooses to accept or discard the new solution with a probability based on its improvement or degradation of key performance indicators.

Bredström and Rönnqvist (2008) describe how the one-to-one LTSP is a derivation of their proposed VRP with temporal precedence and synchronization constraints, for which they derive a MILP formulation. This is first resolved directly with a commercial solver; second by means of a heuristic that iteratively assigns trucks to origin-destination pairs, and then reoptimizes a restricted MILP with these assignments fixed in order to improve the best known solution.

VTM (Virtual Transportation Manager) was developed by researchers at FPInnovations and FORAC Research Consortium in Québec, Canada. The embedded optimization procedure heuristically builds routes and uses constraint programming (CP) to test their feasibility. Audy et al. (2013) describe the implementation and test on a case study in the Canadian context, reporting savings of 7-10%.

Branch-and-price based approaches have been applied to the LTSP; Carlsson and Rönnqvist (2007) outline the implementation on a many-to-many problem with no vehicle fleet assumptions: the goal is to identify backhaul opportunities. Palmgren et al. (2003) consider a heterogeneous fleet and use a pre-generated pool of columns (vehicle routes), found by heuristic enumeration, from which to enrich the LP. They later extended this methodology (Palmgren et al., 2004) to use DP to solve a k-shortest path problem. In both cases integer feasible solutions were found heuristically. Rey et al. (2009) also used DP in the subproblem and, upon resolution of the LP relaxation, solved the MILP through branch-and-bound.

Many of the above contributions do add loader assignment variables to their problem formulation, for example assigning loaders on forest areas on a daily basis, then imposing the constraint that a loader must be present for a truck to load wood. This is a case of operation synchronization (Drexl, 2012). However, very few approaches seen in the literature model this as resource synchronization in the following manner: imposing precisely that a loader can only unload one truck at a time, which yields a much more difficult optimization problem. This can be a crucial aspect in practice, as it allows for minimization of queuing costs that arise when multiple trucks arrive to (un)load at the same time to the same loader. Weintraub et al. (1996) mention that in a traditional, manual management scheme that frequently loaders would be idle for a long time, following which many trucks would arrive simultaneously, leading to long queues. The authors describe the ASICAM ("Asignador des Camiones") DSS, developed at the Universidad de Chile, that provides a working schedule of all trucks for the following day. This uses a simulation-based method that assigns loads to trucks on a moving time horizon, and hence derives an operating schedule for each loader. The authors report using the system on problems with up to 220 trucks, 40 origins, and 15 destinations, and compared to manual planning realized cost savings of 15-35% with additional qualitative improvements in schedules for drivers and loader operators.

El Hachemi et al. (2011) present a daily one-to-one LTSP, which uses linear programming for routing decisions (assigning flows to trucks) and CP for the scheduling decisions to synchronize with loaders. In addition to vehicle costs, they add to their objective the costs associated with each loader, based on the times of the first and last deliveries each day. The authors solve problems with up to 6 supply points, 5 demand points, 18 trucks, and a gross volume of 70 truckloads.

El Hachemi et al. (2013) define a weekly many-to-many problem, which adds a preliminary phase of determining open forest areas and the set of one-to-one requests to perform each day. This first phase is solved with tabu search, and the seven daily problems can then be solved sequentially. For the daily problems, the authors use constraint-based local search (routing and scheduling) and CP (scheduling). This weekly LTSP was then extended to include depot locations for the trucks and mandatory driver lunch breaks (El Hachemi et al., 2014). The algorithm of the first phase used to derive the daily problems was reused from El Hachemi et al. (2013), and the daily problems were then modeled as MILPs and solved with a branch-and-bound solver. These methodologies were applied to case studies up to a size of 6 supply points, 5 demand points, 32 trucks, and a gross volume of 700 truckloads.

CHAPTER 3

ARTICLE 1: A TRANSPORTATION-DRIVEN APPROACH TO ANNUAL HARVEST PLANNING

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Chapter Notes

The contents of this chapter were submitted for publication to the special issue *Advances in Transportation and Logistics* of *Transportation Research Part C: Emerging Technologies* on April 30, 2014. A technical report is available with the CIRRELT (Rix et al., 2014). Preliminary work was a finalist in the Otto Mass poster competition at the 1st Annual FIBRE Conference, and presented at the following conferences:

- 2012 Winter Meeting of the Canadian Mathematical Society
  - December 2012: Montréal, QC, Canada
- Optimization Days 2013
  - May 2013: Montréal, QC, Canada
- 1st Annual FIBRE Conference
  - May 2013: Cornwall, ONT, Canada
- 55th Annual Conference of the Canadian Operational Research Society
  - June 2013: Vancouver, BC, Canada
- 8th Triennial Symposium on Transportation Analysis
  - June 2013: San Pedro de Atacama, Chile
- 15th Symposium for Systems Analysis in Forest Resources
  - August 2013: Québec, QC, Canada

Abstract

Supply chain planning in the forestry industry includes a wide range of decisions, with time horizons ranging from real-time operational problems to long-term strategic problems. When forest companies plan over a length of approximately one year, referred to as the tactical stage of planning, the decisions commonly made are the schedules of forest sites to be visited by harvest teams in order to produce enough volume to meet all demands over the horizon, and also the allocation of this volume to the different demand points. This allocation allows for an estimation of transportation costs, with more detailed routing and scheduling decisions left for operational planning.

The problem described in this article generalizes this tactical problem to include routing decisions, and hence falls into the classes of production routing problems and pickup and delivery problems. This formulation was motivated by an industrial partner, whose goal is to ensure that they have a reliable source of permanent fleet drivers. In order to do this, they must be able to guarantee a variety of different schedules to several trucking contractors whom they hire drivers from, and harvest team scheduling has been identified as more flexible in order to accommodate this requirement. Additionally, significant savings in transportation costs can arise from determining a plan that emphasizes the creation of backhaul opportunities of a heterogeneous set of products. We model this problem as a mixed integer linear program and develop an effective branch-and-price based heuristic capable of generating solutions to medium sized problems in reasonable execution time. Compared to a decomposed and sequential optimization scheme that more accurately represents current industry practice, this methodology is able to fulfil higher demand levels while decreasing transportation costs by an average of $1.41 per cubic meter, or 12.4%.

Keywords: Forestry, transportation, inventory-routing problem, pickup-and-delivery problem, integer programming, column generation

3.1 Introduction

Canada has approximately 400 million hectares of tree cover, and the forest sector contributed to 1.1% of national gross domestic product (Natural Resources Canada). With 146.7 million cubic meters of harvest in 2011, transportation expenses represent a multi-billion dollar expense for Canadian forestry companies (Canadian Council of Forest Ministers). In the context of an economy of this scale, small relative reductions in transportation costs can represent substantial savings. Therefore, the use of optimization models and decision support systems is of high importance, and in recent years research initiatives pursuing these models have been highly prioritized.

We present here a problem that arises in the Canadian forestry industry in tactical planning; in our context this refers a planning horizon of one fiscal year. The decisions commonly made at this level of forest planning are the schedules of harvest teams, storage decisions, and the allocation each month of volume from supply points to demand points. This is a demand-driven problem based on the needs of a heterogeneous set of products at the mills to be served, and a host of industry-specific constraints must be respected in this plan.

While most tactical plans consider these production and allocation decisions, little emphasis is placed on the routing decisions that will be encountered by planners in short term operational planning. The formulation proposed in this article considers generalizing the tactical model to include routing decisions, and we list three reasons for considering this more robust plan. First, a critical component of operations in Canadian forestry companies is to guarantee a variety of different driver schedules to their trucking contractors throughout the year. These schedules differ based on the number of hours per shift worked and the number of shifts worked per month, based on the driver preferences which often vary by season for the same driver. In Canada, the demand for drivers is high with multiple industries competing for services; hence delivering these schedules is a necessity in order to ensure a reliable source of permanent drivers. Second, transportation costs represent a very significant portion of the total cost of the wood supply chain, with 36% being a reported average in the Canadian context (Audy et al., 2012). Therefore optimizing backhaul opportunities is a major priority when scheduling wood procurement at the operational level, and we look to measure the potential savings if we can plan the harvest to optimize future backhaul opportunities. Third, most companies have their wood delivered via a heterogeneous truck fleet, thus necessitating synchronizing transportation decisions with harvest planning with respect to the length into which harvested timber is cut.

While it is very time consuming to formulate a complete annual plan by hand, this is what is done in many companies. Moreover, it is often the case that a plan must be revised due to unexpected events. Therefore the goal was to create a DSS that can be used to formulate a complete plan in a short computational time, with the option to easily modify inputs to generate several different scenarios if needed. Detailed reports must be given in the form of an Excel workbook, including the schedules and volumes produced by each harvest team, and the set of schedules assigned to each trucking contractor throughout the year.

Our contributions in this paper are a model and methodology for solving the problem. We first model this generalized tactical problem as a MILP, and give two related formulations. To our knowledge these are the first formulations applied to the forest supply chain that enforce routing decisions in a tactical harvest planning problem. We next develop a branch-and-price heuristic capable of generating quality solutions in a reasonable time limit. We compare this methodology to a decomposed approach that first schedules the harvest while allocating flows to contractors, and then iteratively generates schedules for the trucks. This allows us to measure the benefits of incorporating these routing decisions at this stage of planning.

In Section 3.2, we describe the problem in more detail. In Section 3.3, we present a mathematical formulation of the problem. Section 3.4 gives the details behind the branch-and-price heuristic used to solve the problem. In Section 3.5, we present the adaptation of the formulation that more accurately reflect current industry practices and will be used for comparative purposes. In Sections 3.6 and 3.7, we discuss the case studies that motivated this paper and the experimental results. Finally, Section 3.8 concludes the paper.

3.2 Problem Definition

We consider the following activities of the value chain: harvesting and forwarding in the forest, roadside wood inventory, transportation, and mill inventory. Additionally, we include the use of intermediate storage locations (remote pits) where wood can be stored before arriving to the mill. These pits usually act as demand nodes in the winter, having their inventory replenished from the forest areas. Then in the spring and summer, when it is more difficult or impossible to traverse much of the transportation network with heavy log-trucks, the pits act as supply nodes serving the mills.

The planning horizon over which we work is one year, with monthly demands and inventory requirements at each mill and pit. These demands exist for each of a set of different log assortments, which may differ with respect to diameter, species, quality, freshness, or other characteristics. All volumes are measured in cubic meters and are based on estimates made by the company.

The total forest management area is partitioned into a set of planning units, and the units that will be harvested are pre-selected at the start of the planning horizon rather than the total available forest management area; this is to avoid creaming of the supply points. If this was not the case, and supply was significantly greater than demand, an optimization model would always choose the supply points that are closest and the average distances would increase over time. In practice, supply is generally chosen to be up to 25% greater than demand, to allow for fluctuations that may arise over the year.

Each planning unit contains a set of subunits which differ in terms of seasonal availability throughout the year. Our harvest decisions are made at the subunit level, which are an aggregation of 3-15 cut blocks to draw parallels with harvest scheduling literature. The company that motivated this research currently derives their annual allocations at the subunit level; with internal cut block sequencing determined by the harvest contractors and potential operational constraints that arise over the course of the year. Subunits may also differ from each other in terms of their priority: it is important to harvest high priority subunits as soon as possible for any number of reasons, including conflict with caribou hunting seasons or the need to coordinate with other industries such as oil mining. Any roadside inventory in the forest that exists prior to the start of the year must be hauled by the end of the year.

A set of harvest teams is defined, and each harvest team has a capacity measured in cubic meters of harvest per month. This may vary per month due to seasonal access restrictions and holiday time. When a team is assigned to a subunit, it must not leave until the entire standing volume is harvested. Additionally, each assortment can be harvested in a choice of lengths ranging from 32 foot to full tree lengths, and the team must be told the proportion of harvest to produce in each length. We emphasize here that this optimization model only considers lengths as they relate to the transportation constraints, and that mill demands can be satisfied with any length of timber in this planning context. This is in contrast other contributions in cut-to-length harvest planning (Chauhan et al., 2011; Dems et al., 2013), in which customer end demands and profitability affect the bucking optimization.

Several trucking contractors are used to transport the harvested timber. Each contractor has a set of schedules, defined by the truck class, the shift length in hours, and the cumulative working days each month (based on the number of drivers and the days worked by each driver). Each shift assigned to a particular schedule must start and end at the location representing the home base of the contractor that month, and alternate between supply nodes (forests or pits) and demand nodes (pits or mills) before ending the shifts. For model feasibility purposes, we define each shift by a maximum and minimum target shift length as opposed to a single number. For example, a specific schedule could specify 100 shifts (for example, an aggregation of 5 drivers working 20 shifts) of between 11 and 14 hours in July. The assignment of the 100 shifts to 5 drivers would be beyond the scope of the optimization model; however if these drivers were chosen to be aggregated then any such assignment would be feasible. Every truck class is only compatible with specific log assortments and lengths, and has a fixed capacity in cubic meters.

The harvest teams and trucking contractors are each assigned a priority: it is most important to give the high priority contractors their desired workload over the course of the year, with the remaining necessary work assigned to lower priority contractors.

3.3 Model Formulation

The model consists of input data, decision variables, an objective function, and constraints. The input data appears in Tables 3.1 through 3.3 and the decision variables are listed in Table 3.4.

3.3.1 Objective Function

Our objective function contains 7 components that contribute to the total cost of a solution. The first and second components are the real costs associated with transportation and storage. The third component is a penalty associated with the total volume produced by each harvest team compared to their desired production. The fourth component is a penalty associated with unsatisfied requested hours on each trucking schedule. The fifth through seventh components are the penalty costs associated with failure to meet demand, failure to meet inventory requirements, and the costs associated with discarding wood at the end of the planning horizon by failing to meet the freshness constraints. These components are listed in Table 3.5.

3.3.2 Constraints

All of the constraints of the model are listed in this section.

Inventory

Constraints (3.1) fix the initial inventories at every node. Constraints (3.2) and (3.3) impose the minima and maxima at each mill and pit each period.

$$w_{nkl1} = i_{nkl}, \forall n \in N, \tag{3.1}$$

$$\sum_{l \in L_k} w_{nklp} + w'_{nkp} \geq i^{min}_{nkp}, \forall n \in N^{in}, k \in K, p \in P, \tag{3.2}$$

$$\sum_{k \in K} \sum_{l \in L_k} w_{nklp} \leq i^{max}_{n}, \forall n \in N^{in}, p \in P. \tag{3.3}$$

Table 3.1 Input Sets

Notation	Representation
$P = \{1, 2, \ldots, \lvert P\rvert\}$	Set of planning periods
$P' = \{1, 2, \ldots, \lvert P\rvert + 1\}$	Set of planning periods including dummy period for next horizon
F	Set of forest planning units
S_f	Set of subunits of forest f
$S = \bigcup_{f \in F} S_f$	Set of all subunits
M	Set of mills
R	Set of remote pits
K	Set of log assortments
L_k	Set of lengths for assortment k
$N = M \cup R \cup S$	Set of all nodes
$N^{in} = M \cup R$	Set of all demand nodes
$N^{out} = S \cup R$	Set of all supply nodes
H	Set of all harvest teams
T	Set of all trucking schedules
Θ_t	Set of all feasible routes for schedule t
$\Theta = \bigcup_{t \in T} \Theta_t$	Set of all routes

Flow Conservation

Constraints (3.4) through (3.6) are flow conservation constraints at mills, forests, and pits.

$$w_{mklp} + \sum_{n \in N^{out}} \sum_{t \in T} x_{nmklpt} - \hat{d}_{mklp} = w_{mkl(p+1)}, \qquad \forall m \in M, k \in K, l \in L_k, p \in P, \tag{3.4}$$

$$w_{sklp} - \sum_{n \in N^{in}} \sum_{t \in T} x_{snklpt} + \sum_{h \in H} v_{hspkl} = w_{skl(p+1)}, \qquad \forall s \in S, k \in K, l \in L_k, p \in P, \tag{3.5}$$

$$w_{rklp} + \sum_{s \in S} \sum_{t \in T} x_{srklpt} - \sum_{m \in M} \sum_{t \in T} x_{rmklpt} = w_{rkl(p+1)}, \qquad \forall r \in R, k \in K, l \in L_k, p \in P. \tag{3.6}$$

Stockout

Constraints (3.7) and (3.8) impose that we never have stockouts at forests and penalize stockout at mills: a mill must always be able to meet its demand, else a penalty is accrued,

Table 3.2 Input Data

Notation	Representation
g_{sk}	Volume of assortment k in subunit s available to harvest
$g_s^{total} = \sum_{k \in K} g_{sk}$	Volume of all assortments in subunit s available to harvest
d_{mkp}	Demand of assortment k at mill m in period p
i_{nkl}	Initial inventory of assortment k in length l at node n
i_n^{max}	Maximum capacity at demand node n
i_{nkp}^{min}	Minimum capacity of assortment k at demand node n in period p
c_n	Loader capacity at demand node n in loads per period
c_{hp}	Harvesting capacity of team h in period p
$C_h = \sum_{p \in P} c_{hp}$	Target production volume for team h over horizon
e_{hsp}	Number of periods for team h to harvest subunit s if commencing in period p
a_{hsp}	Binary parameter equals 1 iff team h can harvest subunit s in period p based on seasonal availability of subunit and team
$\alpha_{hsp} = \prod_{i=p}^{\min\{\lvert P \rvert, p+d_{hsp}-1\}} a_{hsp}$	Binary parameter equals 1 iff team h can begin harvest of subunit s in period p
β_s	Latest period in which subunit s can have remaining standing volume
c_{tkl}	Capacity of assortment k of length l on truck used in schedule t
b_{tp}	Binary parameter equals 1 iff schedule t is available in period p
h_t^{min}	Minimum hours per shift for schedule t
h_t^{max}	Maximum hours per shift for schedule t
d_{tp}	Cumulative requested working days for schedule t in period p
$\rho_{\theta n_1 n_2 kl}$	Number of trips on route θ carrying assortment k in length l from node n_1 to node n_2
h_θ	Shift length (in hours) of route θ

Table 3.3 Costs and Penalties

Notation	Representation
$\gamma_t^{transport}$	Per hour cost of operating (driving, loading, unloading) truck on schedule t
$\gamma_{np}^{holding}$	Cost per m^3 of inventory at node n in period p
$\gamma_h^{harvest}$	Cost per m^3 of shortfall from desired horizon volume of harvest team h
γ_t^{truck}	Cost per unsatisfied shift for trucking schedule t
γ_{mkp}^{demand}	Cost per m^3 of missed demand of assortment k at mill m in period p
$\gamma_{nkp}^{inventory}$	Cost per m^3 of missed minimum inventory of assortment k at demand node n in period p
$\gamma_{nkl}^{freshness}$	Cost per m^3 of discarded product k of length l at supply node n

Table 3.4 Variables

Notation	Representation
$x_{n_1 n_2 klpt} \in \mathbb{R}_{\geq 0}$	Volume of flow of assortment k of length l from supply node n_1 to demand node n_2 in period p on schedule t
$w_{nklp} \in \mathbb{R}_{\geq 0}$	Harvested volume of assortment k of length l stored at node n at the start of period p in P'
$\hat{d}_{mklp} \in \mathbb{R}_{\geq 0}$	Volume of length l used to fill demand at mill m of assortment k in period p
$d'_{mkp} \in \mathbb{R}_{\geq 0}$	Volume of missed demand of assortment k at mill m in period p
$w'_{nkp} \in \mathbb{R}_{\geq 0}$	Volume of missed inventory of assortment k at demand node n in period p
$f'_{nkl} \in \mathbb{R}_{\geq 0}$	Discarded volume of length l of assortment k at supply node n at the end of the planning horizon
$y_{hsp} \in \mathbb{B}$	Equals 1 iff harvest team h commences harvesting subunit s in period p
$\hat{v}_{skl} \in [0, 1]$	Proportion of harvested volume of assortment k from subunit s cut into length l
$v_{hspkl} \in \mathbb{R}_{\geq 0}$	Volume of assortment k of length l produced by harvest team h at subunit s in period p
$z_s \in \mathbb{R}_{\geq 0}$	Period in which subunit s has all remaining standing volume harvested
$L_{np} \in \mathbb{R}_{\geq 0}$	Number of trucks loaded and/or unloaded at node n in period p
$q_{\theta p} \in \mathbb{Z}_{\geq 0}$	Number of times route θ is traversed in period p

Table 3.5 Objective Function Components

Name	Formula
$Z^{transport}$	$\sum_{p \in P} \sum_{\theta \in \Theta} \gamma_t^{transport} h_\theta q_{\theta p}$
$Z^{storage}$	$\sum_{n \in N} \sum_{k \in K} \sum_{l \in L_k} \sum_{p \in P'} \gamma_{np}^{storage} w_{nklp}$
$Z^{harvest}$	$\sum_{h \in H} \gamma_h^{harvest} \left(C_h - \sum_{s \in S} \sum_{p \in p} \sum_{k \in K} \sum_{l \in L_k} v_{hspkl} \right)$
Z^{truck}	$\sum_{t \in T} \sum_{p \in P} \gamma_t^{truck} \left(d_{tp} - \sum_{\theta \in \Theta_t} q_{\theta p} \right)$
Z^{demand}	$\sum_{m \in M} \sum_{k \in K} \sum_{p \in P} \gamma_{mkp}^{demand} d'_{mkp}$
$Z^{inventory}$	$\sum_{n \in N^{in}} \sum_{k \in K} \sum_{p \in P} \gamma_{nkp}^{inventory} w'_{nkp}$
$Z^{freshness}$	$\sum_{n \in N^{out}} \sum_{k \in K} \sum_{l \in L} \gamma_{nkl}^{freshness} f'_{nkl}$

and a forest can never supply more than it has in inventory entering the given period.

$$\sum_{l \in L_k} \hat{d}_{mklp} + d'_{mkp} = d_{mkp}, \forall m \in M, k \in K, p \in P, \tag{3.7}$$

$$\sum_{n \in N^{in}} \sum_{t \in T} x_{snklpt} \leq w_{sklp}, \forall s \in S, k \in K, l \in L_k, p \in P. \tag{3.8}$$

Freshness

Constraints (3.9) are freshness constraints that impose that all roadside inventory at the start of the planning horizon must be hauled by the end of the horizon, else a penalty is accrued.

$$\sum_{n_2 \in N^{in}} \sum_{p \in P} \sum_{t \in T} x_{n_1 n_2 klpt} + f'_{n_1 kl} = w_{n_1 kl1}, \forall n_1 \in N^{out}, k \in K, l \in L_k. \tag{3.9}$$

Harvest

Constraints (3.10) impose that a subunit can only be harvested once and by one team.

$$\sum_{h \in H} \sum_{p \in P} y_{hsp} \leq 1, \forall s \in S. \tag{3.10}$$

Constraints (3.11) impose that there be only one harvest team per forest unit at a time.

$$\sum_{h \in H} \sum_{s \in S_f} \sum_{i=0}^{\min\{p-1, e_{hsp}-1\}} y_{hs(p-i)} \leq 1, \forall f \in F, p \in P. \tag{3.11}$$

Constraints (3.12) impose that a contractor can only a harvest a subunit when allowed.

$$y_{hsp} \leq \alpha_{hsp}, \forall h \in H, s \in S, p \in P. \tag{3.12}$$

Constraints (3.13) impose that a team can only harvest one subunit at a time.

$$\sum_{s \in S} \sum_{p'=0}^{p} \mathbb{1}(p' + e_{hsp'} - 1 \geq p) y_{hsp'} \leq 1, \forall h \in H, p \in P. \tag{3.13}$$

Constraints (3.14) impose that if harvested, a subunit must be either fully cleaned or be cleaned up to contractor capacity until the end of the horizon.

$$\sum_{p \in P} \sum_{k \in K} \sum_{l \in L_k} v_{hspkl} \geq \sum_{p \in P} \min\left(g_s^{total}, (|P| - p + 1) c_{hp}\right) y_{hsp}, \forall h \in H, s \in S. \tag{3.14}$$

Constraints (3.15) impose that the harvested volume from a subunit is bounded by team capacity.

$$\sum_{k \in K} \sum_{l \in L_k} v_{hspkl} \leq c_{hp} \sum_{p'=0}^{p} \mathbb{1}(p' + e_{hsp'} - 1 \geq p) y_{hsp'}, \forall h \in H, s \in S, p \in P. \tag{3.15}$$

Constraints (3.16) impose that the total horizon volume from a subunit is bounded by what is available.

$$\sum_{h \in H} \sum_{p \in P} \sum_{l \in L_k} v_{hspkl} \leq g_{sk}, \forall s \in S, k \in K. \tag{3.16}$$

Constraints (3.17) impose that if nothing is harvested, the team cannot be assigned.

$$\sum_{p'=0}^{p} \mathbb{1}(p' + e_{hsp'} - 1 \geq p) y_{hsp'} \leq \sum_{k \in K} \sum_{l \in L_k} v_{hspkl}, \forall h \in H, s \in S, p \in P. \tag{3.17}$$

Constraints (3.18) impose that the proportions of lengths produced from a particular assortment add up to at most 100% of available volume.

$$\sum_{l \in L_k} \hat{v}_{skl} \leq 1, \forall s \in S, k \in K. \tag{3.18}$$

Constraints (3.19) impose that all lengths not assigned to that subunit cannot be produced.

$$\sum_{h \in H} \sum_{p \in P} v_{hspkl} \leq g_{sk} \hat{v}_{skl}, \forall s \in S, k \in K, l \in L_k. \tag{3.19}$$

Constraints (3.20) impose that no length is produced if nothing is harvested.

$$\hat{v}_{skl} \leq \sum_{h \in H} \sum_{p \in P} v_{hspkl}, \forall s \in S, k \in K, l \in L_k. \tag{3.20}$$

Constraints (3.21) disallow the situation of harvest teams producing at full capacity during periods i and $i+2$ in the same subunit, but partial capacity during period $i+1$, in order to optimize contractor satisfaction. Thus we force a contractor to work at full capacity during all intermediate periods:

$$\sum_{k \in K} \sum_{l \in L_k} \sum_{p'=p+1}^{p+e_{hsp}-2} v_{hsp'kl} \geq \left(\sum_{p'=p+1}^{p+e_{hsp}-2} c_{hp'} \right) y_{hsp}, \forall h \in H, s \in S, p \in P, e_{hsp} \geq 3. \tag{3.21}$$

Constraints (3.22) link the z_s variables, that determine the period in which a subunit is fully harvested, to the formulation. Constraints (3.23) then bound these variables when necessary.

$$2|P| \left(1 - \sum_{h \in H} \sum_{p \in P} y_{hsp} \right) + \sum_{h \in H} \sum_{p \in P} \left(p + e_{hsp} - 1 \right) y_{hsp} = z_s, \forall s \in S, \tag{3.22}$$

$$z_s \leq \beta_s, \forall s \in S. \tag{3.23}$$

Trucking

Constraints (3.24) impose that there must be enough trucks working to accommodate flow. We emphasize that this is modeled as an inequality due to volumes being expressed in cubic meters rather than truckloads due to the heterogeneous truck fleet.

$$\sum_{t \in T} \sum_{\theta \in \Theta_t} c_{tkl} \rho_{\theta n_1 n_2 kl} q_{\theta p} \geq x_{n_1 n_2 klpt}, \qquad \forall n_1 \in N^{out}, n_2 \in N^{in}, k \in K, l \in L_k, p \in P. \tag{3.24}$$

Constraints (3.25) respect the schedule maximum each period.

$$\sum_{\theta \in \Theta_t} q_{\theta p} \leq d_{tp}, \forall t \in T, p \in P. \tag{3.25}$$

Constraints (3.26) through (3.28) determine and constrain loader usage.

$$\sum_{\theta \in \Theta} \sum_{k \in K} \sum_{l \in L_k} \sum_{n \in N^{out}} \rho_{\theta nmkl} q_{\theta p} = L_{mp}, \forall m \in M, p \in P, \tag{3.26}$$

$$\sum_{\theta \in \Theta} \sum_{k \in K} \sum_{l \in L_k} \left(\sum_{s \in S} \rho_{\theta srkl} + \sum_{m \in M} \rho_{\theta rmkl} \right) q_{\theta p} = L_{rp}, \forall r \in R, p \in P, \tag{3.27}$$

$$L_{np} \leq c_n, \forall n \in N^{in}, p \in P. \tag{3.28}$$

Mathematical Formulation

The complete mathematical formulation of the model, which we denote as problem (P1), is then the minimization of the objective function

$$\begin{aligned} Z = Z^{storage} + Z^{transport} + Z^{harvest} + Z^{truck} \\ + Z^{demand} + Z^{inventory} + Z^{freshness} \end{aligned}$$

subject to constraints (3.1) through (3.28).

3.3.3 A Reformulation for More Accurate Harvest Planning

A key issue that arose during preliminary experimentation is that the current formulation does not allow a team to work in more than one subunit in a single period, regardless of whether they have the remaining capacity to do so. Therefore we allow harvesting of any subunit to be done in one of exactly two patterns: where teams produce at partial capacity during either the terminating or commencing period of harvest of a single subunit. In these periods of partial capacity, the team is free to work in up to 2 different subunits. During all other periods, the team is working at full capacity. We introduce two new families of variables, respectively y^1_{hsp} and y^2_{hsp}, that represent the two aforementioned patterns. Constraints (3.29) link the new families of variables to the variables y_{hsp}.

$$y_{hsp} = y^1_{hsp} + y^2_{hsp}, \forall h \in H, s \in S, p \in P. \tag{3.29}$$

Constraints (3.30) and (3.31) enforce the appropriate production for the given patterns:

$$\sum_{k \in K} \sum_{l \in L_k} v_{hspkl} \geq c_{hp} y^1_{hsp}, \forall h \in H, s \in S, p \in P, \tag{3.30}$$

$$\sum_{k \in K} \sum_{l \in L_k} v_{hs(p+e_{hsp}-1)kl} \geq c_{h(p+e_{hsp}-1)} y^2_{hsp}, \forall h \in H, s \in S, p \in P. \tag{3.31}$$

Finally, we replace constraints (3.13) and (3.14) with constraints (3.32) and (3.33), stipulating that a team can be in up to 2 subunits in a given period,

$$\sum_{s \in S} \sum_{p'=0}^{p} \mathbb{1}(p' + e_{hsp'} - 1 \geq p) y_{hsp'} \leq 2, \forall h \in H, p \in P, \tag{3.32}$$

but only 1 when producing at full capacity.

$$\begin{aligned} \sum_{s \in S} \Bigg(\sum_{p'=0}^{p} \mathbb{1}(p' + e_{hsp'} - 2 \geq p) y^1_{hsp'} + \\ \sum_{p'=0}^{p-1} \mathbb{1}(p' + e_{hsp'} - 1 \geq p) y^2_{hsp'} \Bigg) \leq 1, \forall h \in H, p \in P. \end{aligned} \tag{3.33}$$

It is then trivial to determine whether the team harvesting subunits s_1 in period p and s_2 in period $p_2 = p + d_{hs_1p} - 1$ has the capacity to harvest both remainder volumes in the period p_2. We define the binary parameter $g_{hs_1s_2p}$ to this effect.

$$g_{hs_1s_2p} = \begin{cases} 1 & \left(g^{total}_{s_1} + g^{total}_{s_2} - \sum_{p'=p}^{p_2-1} c_{hp'} - \sum_{p'=p_2+1}^{p_2+e_{hs_2p_2}-1} c_{hp'} \right) \leq c_{hp_2} \\ 0 & \text{Otherwise.} \end{cases}$$

Constraints (3.34) allow a team producing at partial capacity to move from one subunit to another, provided the total production is sufficiently low.

$$y^1_{hs_1p} + y^2_{hs_2(p+e_{hs_1p}-1)} \leq 1 + g_{hs_1s_2p}, \forall h \in H, s_1, s_2 \in S, p \in P. \tag{3.34}$$

Constraints (3.35) are required to enforce harvest team capacity per period; in this formulation we must sum these constraints over all subunits in order to account for teams potentially working in multiple harvest locations per period.

$$\sum_{s\in S}\sum_{k\in K}\sum_{l\in L_k} v_{hspkl} \leq c_{hp}, \forall h \in H, p \in P. \tag{3.35}$$

We denote the problem (P2) as the minimization of the objective function Z subject to constraints (3.1) through (3.12) and (3.15) through (3.35).

3.4 Methodology

The biggest obstacle in formulating the model in this matter is the exponential number of variables representing log-truck routes. Hence we use a branch-and-price based methodology in which we start with an empty pool of routes and generate improving ones a priori. The column generation procedure is adapted from the one used by Rix et al. (2015).

3.4.1 Initial Restricted Problem

We first relax the problem (P1) to a linear model to be solved via column generation. Since our initial route set Θ is empty, we additionally relax constraints (3.24) to a soft constraint and give any violation a large penalty in the objective function. This restricted master problem is denoted (P').

After solving the linear relaxation of (P'), we store the dual values associated with constraints (3.24) through (3.27); which we denote $\lambda_{n_1n_2klpt}$, π_{tp}, σ^M_{mp} and σ^R_{rp}, respectively. Our search then begins for negative reduced cost columns with which to enrich the model to improve the objective value of the optimal solution. We propose to find these columns by performing a set of dynamic programming algorithms: one for period p, and for each truck schedule t.

3.4.2 Enriching the Model with Column Generation

To solve these subproblems, we must first construct a space-time network, which we denote $G_{tp} = (N_{tp}, A_{tp})$, for the given schedule and period. We discretize the time dimension, whose horizon ranges from 0 to h^{max}_t, into ω intervals of length $\delta = h^{max}_t/\omega$. We denote this discretized time dimension $I = \{i_0, i_1, \ldots, i_\omega\}$.

We define the network with vertex set

$$V_{tp} = source \bigcup sink \bigcup ((N^{in} \bigcup N^{out}) \times I),$$

where the source and sink nodes correspond to a geographical location where the contractor's trucks are situated. The source node has outgoing arcs to all nodes N^{out}, with the arc originating at time i_0. Similarly, the sink node has incoming arcs from all arcs in N^{in} such that the minimum route length h_t^{min} is respected. The arc set is then $A_{tp} = A_{source} \bigcup A_{sink} \bigcup A_l \bigcup A_u$ where A_{source}, A_{sink}, A_l, and A_u represent out-of-source, into-sink, loaded driving (including loading and unloading time), and unloaded driving arcs, respectively. The cost $c_{n_1n_2}$ of each arc (n_1, n_2) is then easily calculated as a function of per hour operating costs and trucking penalties of that schedule and the distance of the arc.

However in calculating the reduced cost of a route, we modify these arc costs as follows:

$$c_{n_1n_2} \leftarrow \begin{cases} c_{n_1n_2} - \pi_{tp} & (n_1, n_2) \in A_{source}, \\ c_{n_1n_2} & (n_1, n_2) \in A_{sink}, \\ c_{n_1n_2} & (n_1, n_2) \in A_u, \\ c_{n_1n_2} - \lambda_{n_1n_2klpt} - \sigma^M_{n_2p} & (n_1, n_2) \in A_l, n_1 \in S, n_2 \in M, \\ c_{n_1n_2} - \lambda_{n_1n_2klpt} - \sigma^R_{n_1p} - \sigma^M_{n_2p} & (n_1, n_2) \in A_l, n_1 \in R, n_2 \in M, \\ c_{n_1n_2} - \lambda_{n_1n_2klpt} - \sigma^R_{n_2p} & (n_1, n_2) \in A_l, n_2 \in S, n_2 \in R, \end{cases}$$

where we associate with each loaded driving arc (n_1, n_2) in A_l the assortment k and length l that maximize $\lambda_{n_1n_2klp}$. Any feasible route can then be expressed as a source-to-sink path in this network, with the reduced cost of this route equal to the cost of the path.

We note that this network has a clear topological ordering, which is a chronological ordering with ties broken arbitrarily. To find negative reduced cost routes to add to the master problem, we therefore utilize the standard label setting algorithm given by Cormen et al. (1990), in which we associate with each node n a label $[pred_n, RC_n]$ which denotes the predecessor node of n and the length (reduced cost) of the shortest path to n. All nodes only hold one label at any time, except the sink node which holds a set Υ of labels that holds all paths of negative reduced cost. For any schedule t and period p, we provide the details of this algorithm in Figure 3.1. Lines 1 through 4 initialize the labels. Lines 5 through 11 push through the network and update labels as required.

Thus at every master iteration we store the dual values of constraints (3.24) through (3.27), and then solve $|T||P|$ subproblems. All negative reduced cost routes are stored and the columns are added to the master problem. We iterate through this process until no negative reduced cost routes remain or another stopping criterion is achieved.

for all n in N_{tp} **do**
    $pred_n \leftarrow null$
    $RC_n \leftarrow \infty$
$RC_{source} = 0$
for all n_1 in N_{tp} following the topological ordering **do**
    for all (n_1, n_2) in A_{tp} **do**
        if $n_2 = sink$ **and** $RC_{n_1} + c_{n_1 n_2} < 0$ **then**
            $\Upsilon \leftarrow \Upsilon \bigcup \{[n_1, RC_{n_1} + c_{n_1 n_2}]\}$
        if $RC_{n_2} < RC_{n_1} + c_{n_1 n_2}$ **then**
            $RC_{n_2} \leftarrow RC_{n_1} + c_{n_2 n_2}$
            $pred_{n_2} \leftarrow n_1$

Figure 3.1 Shortest Path Algorithm for Routing Subproblem

3.4.3 Column Pool Management

At each iteration, upon the resolution of all subproblems, the most general method would be to add all negative reduced cost columns found to the LP. However many of these routes will prove unnecessary and remain non-basic until the algorithm terminates. As managing the column pool can require a significant amount of computation time when the pool is very large, we utilize two methods to control the size of the column pool. First, at each iteration we simply added the best (most negative reduced cost) 200 columns found. Second, upon passing a predetermined upper limit on pool size, columns are eliminated randomly until a lower limit is achieved (set to 70% of the upper limit).

3.4.4 Heuristic Branch-and-Price

In order to solve our problem to optimality, we would have to embed our column generation procedure into a branch-and-bound tree (Barnhart et al., 1998). However we choose to more quickly find integer feasible solutions through the use of an efficient heuristic branching method motivated by Prescott-Gagnon et al. (2009).

We impose branching decisions on the harvest variables y_{hsp} by fixing the one with the largest fractional value to 1 upon the resolution of an LP. We do not fix variables to 0 as this does not significantly modify the problem. Moreover we do not allow backtracking: branching decisions cannot be reversed. We continue this process until none of these variables that remain unfixed remain with value greater than a parameter ψ in $[0, 1]$.

For the formulation (P2), the branching strategy is analogous on the variables y^i_{hsp}. As an addendum, preliminary experimentation found that the resolution of the LPs slowed considerably when all constraints (34) (cardinality $|H||S|^2|P|$) were initially added to the model. Therefore we only enforce the relevant constraints that become tight after enforcing a branching decision.

To terminate the algorithm and generate an integer feasible solution, we then enforce integrality constraints on all remaining variables that are integral in the MILP formulation, and solve the resulting problem using a branch-and-bound solver.

3.5 Decomposed Approach

To assess the benefit of incorporating routing decisions in tactical planning, we compare the methodology to an implementation that more accurately reflects the current industry practice. We first derive a model that represents the annual harvest plan, giving schedules to the harvest teams, allocating flow to transportation fleets by month, and managing monthly demands and inventory levels. This is a MILP model including most of the variables and constraints of the model developed in Section 4.

For this first phase, we eliminate the $q_{\theta p}$ variables from the above formulations. Let $d(n_1, n_2)$ represent the cycle time of a truck from supply point n_1 to demand point n_2 and back, including loading and unloading times. We replace the $Z^{transport}$ and Z^{truck} terms in the objective function by their flow-based approximations:

$$\begin{aligned} Z_H^{transport} &= \sum_{n_1 \in N^{out}} \sum_{n_2 \in N^{in}} \sum_{k \in K} \sum_{l \in L_k} \sum_{p \in P} \sum_{t \in T} \gamma_t^{transport} \frac{d(n_1, n_2)}{c_{tkl}} x_{n_1 n_2 klpt}, \\ Z_H^{truck} &= \sum_{t \in T} \sum_{p \in P} \gamma_t^{truck} \left(d_{tp} - \sum_{n_1 \in N^{out}} \sum_{n_2 \in N^{in}} \sum_{k \in K} \sum_{l \in L_k} \frac{d(n_1, n_2)}{c_{tkl} h_t^{max}} x_{n_1 n_2 klpt} \right). \end{aligned}$$

We similarly replace constraints (3.25) through (3.27)

$$\sum_{n_1 \in N^{out}} \sum_{n_2 \in N^{in}} \sum_{k \in K} \sum_{l \in L_k} \frac{d(n_1, n_2)}{c_{tkl} h_t^{max}} x_{n_1 n_2 klpt} \leq d_{tp}, \forall p \in P, t \in T, \tag{3.25H}$$

$$\sum_{k \in K} \sum_{l \in L_k} \sum_{t \in T} \sum_{n \in N^{out}} \frac{1}{c_{tkl}} x_{nmklpt} = L_{mp}, \forall m \in M, p \in P, \tag{3.26H}$$

$$\sum_{k \in K} \sum_{l \in L_k} \sum_{t \in T} \frac{1}{c_{tkl}} \left(\sum_{s \in S} x_{srklpt} + \sum_{m \in M} x_{rmklpt} \right) = L_{rp}, \forall r \in R, p \in P. \tag{3.27H}$$

We denote the resulting harvest-flow model by $(PH1)$, in which we minimize the objective function

$$Z_H = Z^{storage} + Z_H^{transport} + Z^{harvest} + Z_H^{truck} \\ + Z^{demand} + Z^{inventory} + Z^{freshness}$$

subject to constraints (3.1) through (3.24), (3.25H) through (3.27H), and (3.28). Analogously to problem ($P2$), we define ($PH2$) to be the minimization of Z_H subject to constraints (3.1) through (3.12), (3.15) through (3.24), (3.25H) through (3.27H), and (3.28) through (3.15).

After solving ($PH1$) or ($PH2$), we can solve the vehicle routing decisions on a rolling horizon basis, as is the case in practice. We let ($x^*_{n_1n_2klpt}$) denote the optimal values of the corresponding variables. We then solve a problem $(PR)_p$ for each period p to determine the optimal routing plan based on the given flow. This is solved by the minimization of $Z_{Rp} = Z_p^{transport} + Z_p^{truck}$ where $Z_p^{transport}$ and Z_p^{truck} are the terms of $Z^{transport}$ and Z^{truck} that represent a single period. We then define constraints (3.36) to fix total wood flow to the optimal values determined in the annual harvest plan:

$$\sum_{t\in T} x_{n_1n_2klpt} \leq \sum_{t\in T} x^*_{n_1n_2klpt}, \forall n_1 \in N_{out}, n_2 \in N^{in}, k \in K, l \in L. \tag{3.36}$$

After solving each routing problem per period, the cumulative objective value is equal to:

$$Z^{storage} + Z^{harvest} + Z^{demand} + Z^{inventory} + Z^{freshness} + \sum_{p\in P} Z_{Rp}.$$

We emphasize that the decomposed methodology of this section more accurately represents the current industry practice, but is in many cases superior to this manual practice. For our purposes, it represents a point of comparison to measure the resulting savings from implementing a routing-based methodology over an annual time horizon.

3.6 Case Studies

This project was motivated by several case studies provided by FPInnovations, a Canadian not-for-profit organization which carries out scientific research and technology transfer for the Canadian forest industry. Three case studies were built out of previous years' historical data provided by an industrial partner in western Canada, which we denote by A, B and C. In all cases, the demand points to be served are a single mill and 4 remote pits. This demand is of 2 log assortments, deciduous and conifer, each of which can be cut into 3 different lengths: 32 foot, 37 foot, and full tree.

Harvested volumes for 8 harvesting contractors, with varying availability and target production each month of the year, were cumulated over the year to generate the information to be used for available supply. Gross harvested volumes ranged from 1.1 to 1.5 million cubic meters, with an additional 0.3 to 0.5 million cubic meters of roadside inventory at the start of the planning year. This represents roughly 20000 to 30000 truckloads, depending on the truck configuration used. Approximately 75% to 85% of the supply is deciduous, with the remainder being conifer.

Average loaded and empty driving times between all supply and demand points were generated from the forest supply chain control platform FPInterface, developed by FPInnovations. Cycle times were generally between 3 and 8 hours.

Demand consumption and inventory requirements were not as readily available in previous years, but were generated by considering forecasted monthly consumption for the following year, and scaling these monthly forecasted volumes to a percentage (given in Section 3.7) the gross supply (standing and roadside) information of the year being optimized.

The same approach was used to generate the requirements of the 7 driver schedules, with varying monthly available working days of shift lengths ranging from 12 to 16 hours and 5 unique truck configurations. The monthly availabilities of the following year were scaled to match the supply and demand information of the previous years.

Storage and transportation costs are easy to measure, and vary from 0 to 2 $\$/m^3$ and 70 to 100 $\$/hr$, respectively. However the other penalties in the objective function are more difficult to measure, but their setting will dramatically affect the final solution. Both harvest and transportation contractors fell into 2 priority classes, and hence the lower priority contractors were assigned a penalty of 0. Based on discussion with industry decision makers and preliminary sensitivity analysis, the other penalties were assigned as follows:

$$\begin{aligned}
\gamma_h^{harvest} &= \$2/m^3, \\
\gamma_t^{truck} &= \$(0.5)(\gamma_t^{transport} h_t^{max})/\text{day}, \\
\gamma_{mkp}^{demand} &= \$60/m^3, \\
\gamma_{mkp}^{inventory} &= \$50/m^3, \\
\gamma_{mkp}^{freshness} &= \$50/m^3.
\end{aligned}$$

3.7 Experimental Results

The program was modeled in C++, with Gurobi Optimizer 5.6.2 (Gurobi Optimization) used as a solver of the master problem. For all LPs, we utilized the included barrier optimizer in order to generate interior solutions and hence more useful dual values. All other Gurobi parameters were set to the default setting.

We chose to discretize the subproblem into intervals of 20 minutes, as that is approximately the degree of accuracy to which we can measure driving distances. All experimentation was done on an Intel Core i7, 2.67 GHz processor with 4.0 GB of memory, with time limit set to 20 minutes.

For each case study we scaled the demand and inventory requirements to represent a percentage of the total supply, iterating over 80% to 90% to 100%, though we note that 80% most accurately reflects the current industry practice. For each of these problem sets we applied 4 methodologies, allowing for both harvest team scheduling formulations (1 and 2) and both the branch-and-price (BP) and decomposed (D) methodologies.

Solution quality was measured based on several key performance indicators. The total objective value was of course important, as well as the total spent on transportation. The percentage of the demand and inventory requirements that were attained, and the percentage of desired work given to both high priority harvest and trucking contractors were measured. To compare Formulation 2 to Formulation 1 with respect to harvest scheduling, the difference between the work levels of high priority harvest contractors was calculated. Cumulating the total volume of hauled wood over the course of the year allows for expression of the transportation cost in dollars per cubic meter delivered, and for each case study and formulation the improvement of the branch-and-price formulation over the decomposed approach was measured in both absolute and relative terms. All results appear in Table 3.6.

It is clear that incorporating routing decisions into the harvest planning model allows us to attain a higher percentage of the requested demand and inventory levels, as the decomposition attains lower levels in all cases. Moreover, by linking these decisions into a single model, the savings generated in transportation costs from planning the harvest to emphasize backhaul routes for the trucks over the planning horizon are significant, with an average value of $1.41 per cubic meter or 12.4%.

With respect to driver satisfaction, in all scenarios the branch-and-price approach gives an average of 98.4% of the requested shifts to high priority drivers; hence the allocated flow generated can then be easily assigned as a guarantee of work over the planning horizon. We note that in two out of three case studies, the decomposed methodology does not perform significantly worse in this regard. However in case study C, the decomposed methodology is outperformed due to poor decisions made in the tactical planning phase with respect to the assignment of flow to months in which the combination of driving distance and wood product are incompatible with the drivers working those months. This situation further illustrates the need to have more detailed vehicle routing decisions taken into account in tactical planning.

Extending the formulation to account for mid-period harvest team movement allows for an increase in the annual harvested volume assigned to high priority harvest teams. In our

Table 3.6 Experimental Results

Case Study	Demand Levels (%)	Harvest Scheduling Formulation	Solution Methodology	Objective Value (million $)	Transportation Cost (million $)	Demand Attained (%)	Inventory Levels Attained (%)	Priority 1 Trucking Attained (%)	Priority 1 Harvest Attained (%)	Formulation 2 Improvement (%)	Annual Haul (m^3)	Transportation Cost ($/$m^3$)	Improvement over Decomposition ($/$m^3$)	Improvement over Decomposition (%)
A	80	1	BP	21.968	18.459	99.94	99.98	99.98	88.26	-	1,539,612	11.99	1.51	12.63
A	80	2	BP	21.908	18.569	99.94	99.99	100	97.42	9.16	1,539,517	12.06	1.84	15.23
A	80	1	D	38.504	18.647	92	95.7	100	90.36	-	1,380,920	13.50	-	-
A	80	2	D	39.660	19.161	91.59	95.04	99.97	94.71	4.35	1,378,647	13.90	-	-
A	90	1	BP	29.096	21.548	95.71	99.99	99.81	88.88	-	1,714,409	12.57	1.20	9.55
A	90	2	BP	29.697	21.293	95.23	99.56	99.98	90.81	1.93	1,699,018	12.53	1.21	9.67
A	90	1	D	45.294	20.418	84.94	96.59	98.11	86.9	-	1,482,841	13.77	-	-
A	90	2	D	46.886	20.562	85.54	95.73	95.59	89.17	2.27	1,496,061	13.74	-	-
A	100	1	BP	42.878	21.294	84.11	98.85	99.98	86.15	-	1,704,574	12.49	1.34	10.74
A	100	2	BP	43.161	21.285	83.67	98.9	100	92.48	6.33	1,686,244	12.62	0.97	7.70
A	100	1	D	62.867	19.996	72.51	96.02	96.27	85.72	-	1,445,512	13.83	-	-
A	100	2	D	62.436	19.504	72.16	94.21	95.46	78.22	-7.50	1,434,679	13.59	-	-
B	80	1	BP	20.730	17.422	99.99	100.00	99.93	75.68	-	1,470,925	11.84	1.13	9.58
B	80	2	BP	20.643	17.377	99.92	99.97	99.93	81.37	5.69	1,477,908	11.76	1.22	10.36
B	80	1	D	24.190	18.342	97.84	98.96	99.99	73.87	-	1,413,189	12.98	-	-
B	80	2	D	23.811	18.465	97.45	99.98	99.99	71.67	-2.19	1,423,037	12.98	-	-
B	90	1	BP	32.099	17.166	86.54	99.73	99.99	75.68	-	1,465,857	11.71	1.43	12.22
B	90	2	BP	31.181	17.614	87.91	99.94	99.94	78.16	2.48	1,500,811	11.74	1.03	8.79
B	90	1	D	35.519	18.583	84.68	99.62	100.00	76.82	-	1,414,056	13.14	-	-
B	90	2	D	35.529	18.613	84.79	99.22	100.00	72.24	-4.58	1,457,706	12.77	-	-
B	100	1	BP	42.951	17.456	76.71	99.71	99.94	75.19	-	1,497,923	11.65	1.51	12.98
B	100	2	BP	42.597	17.517	77.02	99.77	99.96	78.16	2.96	1,494,002	11.72	1.37	11.72
B	100	1	D	46.986	18.635	74.56	98.91	100.00	73.85	-	1,415,364	13.17	-	-
B	100	2	D	48.085	17.958	73.83	98.03	100.00	75.20	1.34	1,370,956	13.10	-	-
C	80	1	BP	19.204	17.127	99.98	99.43	97.24	87.27	-	1,683,723	10.17	1.54	15.13
C	80	2	BP	25.137	16.430	93.56	98.26	89.18	85.61	-1.66	1,568,948	10.47	2.97	28.40
C	80	1	D	30.273	17.805	91.45	98.40	83.30	85.31	-	1,520,460	11.71	-	-
C	80	2	D	35.875	19.782	88.79	97.25	86.76	70.40	-14.91	1,471,222	13.45	-	-
C	90	1	BP	33.847	18.409	88.56	97.76	98.25	88.47	-	1,702,256	10.81	0.60	5.56
C	90	2	BP	26.178	19.298	94.70	98.77	99.46	97.81	9.34	1,816,003	10.63	1.86	17.47
C	90	1	D	36.842	19.080	86.93	97.18	94.06	86.45	-	1,671,492	11.41	-	-
C	90	2	D	58.773	16.872	69.60	95.94	85.49	63.04	-23.41	1,351,531	12.48	-	-
C	100	1	BP	46.528	17.934	78.34	97.64	94.54	85.00	-	1,735,904	10.33	1.32	12.80
C	100	2	BP	45.590	19.277	79.67	97.67	92.94	92.59	7.60	1,758,843	10.96	1.44	13.15
C	100	1	D	54.377	18.869	75.43	96.02	87.30	87.64	-	1,619,111	11.65	-	-
C	100	2	D	49.601	21.425	79.40	96.38	93.70	89.21	1.58	1,727,622	12.40	-	-

branch-and-price based formulation, over all case studies and demand scenarios, this average volume assigned is increased by 4.9%. Though the additional variables and constraints present in this formulation do make the model more computationally difficult, without a significant change in the other costs and penalties of the resulting solution, the trade off appears to be beneficial to the industry decision makers.

3.8 Conclusion

We have introduced a tactical harvest planning model that, unlike prior models in the industry, incorporates vehicle routing decisions along with allocation wood flow decisions in the transportation constraints. This problem was modeled as a MILP, and solved via a branch-and-price heuristic with columns generated by a branch-and-price heuristic. The generated columns represent vehicle routes and are generated via dynamic programming, and the branching decisions are made on the harvest teams, with no backtracking in the search tree.

This has been implemented in a decision support system for use by our research partner FPInnovations, and tested on case studies built from 3 years of historical data of a Canadian forest company. Under an array of demand scenarios, and compared to a decomposed and sequential optimization scheme representing the current industrial practice, we are able to meet a higher proportion of demand and inventory requirements, while decreasing transportation costs by an average of 12.4%.

CHAPTER 4

ARTICLE 2: A COLUMN GENERATION ALGORITHM FOR TACTICAL TIMBER TRANSPORTATION PLANNING

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Chapter Notes

The contents of this chapter were published in the *Journal of the Operational Research Society* (Rix et al., 2015) on January 15, 2014. A technical report is available with the CIRRELT (Rix et al., 2013). Preliminary work was presented at the following conferences:

- Optimization Days 2012
  - May 2012: Montréal, QC, Canada
- 5th International Workshop on Freight Transportation and Logistics
  - May 2012: Mykonos, Greece
- 54th Annual Conference of the Canadian Operational Research Society
  - June 2012: Niagara Falls, ONT, Canada

Abstract

We present a tactical wood flow model that appears in the context of the Canadian forestry industry, and describe the implementation of a decision support system created for use by an industrial partner. In this problem, mill demands and harvested volumes of a heterogeneous set of log types are given over a multi-period planning horizon. Wood can be stored at the forest roadside prior to delivery at a financial cost. Rather than solve this as a network linear program on the basis of out-and-back deliveries, we choose to model this problem as a generalization of a log-truck scheduling problem. By routing and scheduling the trucks in the resolution, this allows us to both anticipate potential backhaul opportunities for cost and fuel savings, and also minimize queuing times at log-loaders, management of which is a major concern in the industry. We model this problem as a mixed integer linear program and solve it via column generation. The methodology is tested on several case studies.

Keywords: Forestry, vehicle routing, decision support system, integer programming, column generation

4.1 Introduction

According to *Natural Resources Canada* (Natural Resources Canada), Canada has approximately 400 million hectares of forest and other wooded land, making up approximately 10% of the world's forest cover. It is therefore unsurprising that Canada is the world's largest exporter of forest products: in 2008 the value of all exports from this industry was over 30 billion dollars. Overall, the forest industry accounts for approximately 2% of national gross domestic product. When dealing with an economy of this scale, it is clear that performing all operations as efficiently as possible can lead to tremendous financial savings. Therefore it is a necessity that the use of optimization models and methods are commonplace in this industry, both for the obvious economic, and also environmental reasons.

Because of the geographical nature of Quebec, transportation accounts for approximately 30% of the total cost of wood. The average distance between the forest where the wood is collected and the mills to which it is delivered is approximately 150 km. However, as significant as this aspect of the supply chain is, most Canadian forest companies have a planner derive the truck schedules manually.

This is changing, and recent emphasis has been put on the development of planning methods and decision support systems in this domain to take advantage of potential savings (Audy et al., 2012). We note three main phases of transportation planning that are focused on in this paper: allocation, routing, and scheduling. Allocation involves making optimal allocations of supply points to demand points in order to minimize hauling distance. Routing involves creating routes for the trucks that allow us to take advantage of backhaul opportunities. Recent advancements in the use of multi-product truck trailers have generated new opportunities in this regard. Finally, scheduling is important in this industry due to unproductive but still expensive truck and driver waiting time (queuing) when coordinating with loading equipment, a problem which is more unique to the forestry industry.

Wood allocation decisions are commonly made at the tactical level of planning, for example when formulating annual harvest and wood flow schedules. When these decisions are already determined, there is much less flexibility when determining truck schedules in operational planning, and perhaps further minimization could be achieved through smarter tactical decisions. It is for this reason that we create a tactical wood flow model that prioritizes routing and scheduling, allowing us to realize additional cost savings.

Thus the contribution of this paper is to define a tactical transportation planning problem over a one year time horizon that incorporates log-truck scheduling elements in order to more accurately minimize transportation costs and queuing times. We then develop a column generation methodology to apply to this problem and give computational results on several industrial case studies. Additionally, we describe the implementation into a decision support system that is in use by an industrial partner.

In Sections 4.2 and 4.3 we define the problem. In Section 4.4 we discuss our methodology. In Sections 4.5 and 4.6 we discuss the case studies that motivated this problem and the computational results. Section 4.7 describes the implementation into a DSS for use by our industrial partner. Finally, Section 4.8 concludes the paper.

4.2 Problem Definition

The problem we consider in this paper is a tactical wood flow model. We assume an annual harvest plan as input, and we will solve a single tactical model of determining the wood flow and storage, while taking into account truck routing and scheduling decisions over the planning horizon. This allows for smarter tactical decisions to be made, through taking advantage of savings generated through optimization of all of allocation, routing and scheduling. While the scenario may change over the year and reoptimization may be necessary on a rolling basis, this still gives a plan for the present that improves the operational planning process in the future.

We assume a multi-period planning horizon, with each period partitioned into a set of working days. We are next given a harvest plan of log assortments at forest sites over this horizon, with these multiple assortments differing in terms of species, quality, length and/or diameter. While these are anticipated future volumes, advancements in scanning of forest stands make these estimates accurate enough for planning purposes. We also assume non-constant but deterministic mill demands over the horizon, though reoptimization may be necessary as demands change over time. Multiple classes of trucks are available to transport the wood, each with a different capacity and loading requirements. We note that different trucks with different capacities implies that volumes must be expressed in cubic meters (m^3), rather than simply truckloads as is common in current literature.

Under the current industrial constraints, some trucks are equipped with onboard loaders and thus do not need to synchronize with a separate loader at the forest; however, every truck must unload its capacity via the equipment based at the mill. Whenever a truck must synchronize with a loader at the forest or mill, if the loader is busy when the truck arrives then the truck must wait, yielding unproductive labor costs. While we do not take into account loader routing or minimization of loader operating costs, we do place an upper bound, per period, on the number of forest sites a loader can be assigned to. Each loader can then only move around within this site, movement that is beyond the scope of this model. By bounding the number of "active" forest sites, we will assist future decision makers by simplifying the operational loader scheduling.

This LTSP is then to determine the quantity of each assortment to deliver from each forest to each mill in each period, the necessary storage between periods at each forest and each mill, the traversal of log-truck routes in order to deliver the produced logs to the mills, and the assignment of log-loaders to forest sites throughout the horizon.

In addition to satisfying mill demands and not exceeding the harvested quantities, several other constraints must be satisfied. There exists a given limit on the length of time wood can remain in the forest. This may vary by period, as wood deteriorates less quickly in the winter than in other seasons. With respect to routing, if a truck is to be used on a specific day, it must begin and end its day at the same mill. The truck then alternates between forest sites where it loads wood, and mills where it then unloads. Truck capacity can not be exceeded, and the truck can not carry different assortments at the same time. Additionally, each mill has operating hours over which it can receive wood. A truck can leave a mill before it opens and return to a mill after it closes; however it will have to wait until the mill is open to unload its load.

A final constraint that is often used is important for planning truck fleet size and satisfying labor constraints: we also must ensure a balanced schedule. That is, each day a minimum and maximum number of daily truck routes must be assigned that do not deviate too far from the mean over the horizon. However, if the inputs of the model are a harvest plan with a large standard deviation of quantity produced per period, these constraints can not be enforced as there must naturally be a correlation between the number of cubic meters to haul and the number of trucks on the road.

4.3 Mathematical Formulation

Let us define F to be the set of forest sites, M to be the set of mills, L to be the set of log assortments, T to be the set of truck classes, P to be the set of periods in the planning horizon, and D_p to be the set of all working days in each period p. Moreover, we must discretize the time dimension of each day into $I = \{i_0, i_1, \dots, i_n\}$, with δ denoting the interval duration between any consecutive i. We then let J be the set of all feasible log-truck routes, every activity of which (driving, (un)loading, and waiting for a loader) has its duration approximated by some multiple of δ. For notational purposes, we partition J by the truck class t and by the mill m at which the route originates and terminates, into J_t, J_m and J_{mt}. The cost of a given route is then easily calculated as a function of per hour operating and waiting costs.

We now define the input data of the model:

h_{flp} = the quantity of assortment l harvested at forest f in period p,

d_{mlp} = the demand of assortment l at mill m in period p,

i^F_{fl} = the initial inventory of assortment l at forest f,

i^M_{ml} = the initial inventory of assortment l at mill m,

w_{flp} = the maximum storage time at forest f of assortment l harvested in period p,

$w_{flpp'} = \mathbb{1}(p' + w_{flp'} \geq p)$ = binary parameter indicating if harvest of assortment l in forest f in period $p' \leq p$ can still remain at roadside in p,

k_{tl} = the capacity of assortment l of truck class t,

$$v_t = \begin{cases} 1 & \text{Truck class } t \text{ requires synchronization with a loader at the forest,} \\ 0 & \text{Truck class } t \text{ is self-loading,} \end{cases}$$

c^F_{flp} = the per unit storage cost of assortment l at forest f in period p,

c^M_{mlp} = the per unit storage cost of assortment l at mill m in period p,

c^J_j = the cost of route j,

c^T_t = the fixed cost of operating a truck of type t on a working day,

a_{fmlj} = the number of trips from forest f to mill m carrying assortment l on route j,

$$L_{jfi} = \begin{cases} 1 & \text{A truck traversing route } j \text{ is loading wood at forest } f \\ & \qquad \text{over interval } i, \\ 0 & \text{Otherwise,} \end{cases}$$

$$U_{jmi} = \begin{cases} 1 & \text{A truck traversing route } j \text{ is unloading wood at mill } m \\ & \qquad \text{over interval } i, \\ 0 & \text{Otherwise.} \end{cases}$$

n^T_{mpt} = the number of available trucks of class t based at mill m in period p,

$\epsilon \in [0, 1]$ = the allowable deviation per period from the mean number of routes,

n^L_p = the number of loaders available in period p to assign to forest sites,

n^L_{mp} = the number of loaders available in period p at mill m.

The variables of the model are given below:

$$
\begin{aligned}
y_{jpd} &= \text{the number of times route } j \text{ is traversed on day } d \text{ in period } p,\\
T_{mpdt} &= \text{the number of daily truck routes based at mill } m \text{ in period } p\\
&\quad\ \text{using truck class } t,\\
z^M_{mlp} &= \text{the quantity of assortment } l \text{ stored at mill } m\\
&\quad\ \text{entering period } p \leq |P|+1,\\
z^F_{flp} &= \text{the quantity of assortment } l \text{ stored at forest } f\\
&\quad\ \text{entering period } p \leq |P|+1,\\
x_{fmlpt} &= \text{the quantity of assortment } l \text{ delivered from forest } f \text{ to mill } m\\
&\quad\ \text{using truck class } t \text{ in period } p,\\
L_{fp} &= \begin{cases} 1 & \text{A loader is assigned to forest } f \text{ in period } p,\\ 0 & \text{Otherwise.} \end{cases}
\end{aligned}
$$

The problem can then be formulated as the minimization of the objective function:

$$
\begin{aligned}
&\sum_{p\in P}\sum_{d\in D_p}\sum_{j\in J} c^J_j y_{jpd} + \sum_{m\in M}\sum_{p\in P}\sum_{d\in D_p}\sum_{t\in T} c^T_t T_{mpdt}\\
&\quad + \sum_{f\in F}\sum_{l\in L}\sum_{p\in P} c^F_{flp} z^F_{flp} + \sum_{m\in M}\sum_{l\in L}\sum_{p\in P} c^M_{mlp} z^M_{mlp}
\end{aligned}
\tag{4.1}
$$

subject to:

$$z^M_{ml0} = i^M_{ml}, \forall\ m \in M, l \in L, \tag{4.2}$$

$$z^F_{fl0} = i^F_{fl}, \forall\ f \in F, l \in L, \tag{4.3}$$

$$z^M_{mlp} + \sum_{f\in F}\sum_{t\in T} x_{fmlpt} - d_{mlp} = z^M_{ml(p+1)}, \forall\ m \in M, l \in L, p \in P, \tag{4.4}$$

$$z^F_{flp} + h_{flp} - \sum_{m\in M}\sum_{t\in T} x_{fmlpt} = z^F_{fl(p+1)}, \forall\ f \in F, l \in L, p \in P, \tag{4.5}$$

$$\sum_{p'=0}^{p} w_{flpp'} h_{flp'} \geq z^F_{flp}, \forall\ f \in F, l \in L, p \leq |P|+1, \tag{4.6}$$

$$\sum_{j\in J_t} k_{tl} a_{fmlj} \sum_{d\in D_p} y_{jpd} \geq x_{fmlpt}, \forall\ f \in F, m \in M, l \in L, p \in P, t \in T, \tag{4.7}$$

$$\sum_{j \in J_{mt}} y_{jpd} = T_{mpdt}, \forall\ m \in M, p \in P, d \in D_p, t \in T \tag{4.8}$$

$$T_{mpdt} \leq n^T_{mpt}, \forall\ m \in M, p \in P, d \in D_p, t \in T \tag{4.9}$$

$$\sum_{m \in M} \sum_{t \in T} T_{mpdt} \geq \frac{1-\epsilon}{\sum_{p' \in P} |D_{p'}|} \sum_{m \in M} \sum_{p' \in P} \sum_{d' \in D_p} \sum_{t \in T} T_{mpdt}, \tag{4.10}$$

$$\forall\ p \in P, d \in D_p,$$

$$\sum_{m \in M} \sum_{t \in T} T_{mpdt} \leq \frac{1+\epsilon}{\sum_{p' \in P} |D_{p'}|} \sum_{m \in M} \sum_{p' \in P} \sum_{d' \in D_p} \sum_{t \in T} T_{mpdt}, \tag{4.11}$$

$$\forall\ p \in P, d \in D_p,$$

$$\sum_{f \in F} L_{fp} \leq n^L_p, \forall\ p \in P, \tag{4.12}$$

$$\sum_{j \in J_t} U_{jmi} y_{jpd} \leq n^L_{mp}, \forall\ m \in M, p \in P, d \in D_p, i \in I, \tag{4.13}$$

$$\sum_{t \in T} v_t \sum_{j \in J} L_{jfi} y_{jpd} \leq L_{fp}, \forall\ f \in F, p \in P, d \in D_p, i \in I, \tag{4.14}$$

$$\sum_{t \in T} v_t \sum_{d \in D_p} \sum_{m \in M} \sum_{l \in L} x_{fmlpt} \leq \Omega L_{fp}, \forall\ f \in F, p \in P, \tag{4.15}$$

$$\sum_{m \in M} \sum_{j \in J_{mt}} \sum_{i \in I} U_{jmi} y_{jpd} \leq \sum_{m \in M} \sum_{j \in J_{mt}} \sum_{i \in I} U_{jmi} y_{jp,d+1}, \tag{4.16}$$

$$\forall\ p \in P, d \leq |D_p| - 1,$$

$$L_{fp} \in \{0, 1\}, \forall\ f \in F, p \in P. \tag{4.17}$$

$$y_{jpd}, T_{mpdt} \in \mathbb{Z}_{\geq 0}, \forall\ m \in M, j \in J_m, p \in P, d \in D_p, t \in T. \tag{4.18}$$

$$z^N_{mlp}, z_{flp}, x_{fmlp} \in \mathbb{R}_{\geq 0}, \forall\ f \in F, m \in M, l \in L, p \in P. \tag{4.19}$$

We denote this problem by (P). The objective function (4.1) minimizes total costs associated with driving and storage. Constraints (4.2) and (4.3) set the initial inventories at the mills and forests, respectively. Constraints (4.4) and (4.5) link the storage variables of successive periods at the mills and forests, respectively. The non-negativity of all variables ensure that forest supply and mill demands are respected. Constraints (4.6) ensure that wood is not left at the forest longer than allowed by forcing the volume in storage in period p to be bounded above by the volume of any prior harvest that is still fresh in p. We note that for these constraints to be valid a first in first out (FIFO) system must be utilized by the drivers, meaning that a driver will always pick up the oldest wood of the specified log assortment.

Constraints (4.7) force the quantity delivered to respect the capacities of all trucks making that trip. Constraints (4.8) fix the number of routes originating from each mill in each period, and constraints (4.9) bound this by the associated availability. Constraints (4.10) and (4.11) ensure a balanced schedule in terms of the number of truck routes traversed at every day of the horizon by bounding it by both the allowed percentage above $(1+\epsilon)$ and below $(1-\epsilon)$ the mean number of routes per day.

Constraints (4.12) limit the total number of loaders assigned to forests in a period. Constraints (4.13) and (4.14) assign each loader to only one truck at any time. Constraints (4.15) are redundant constraints that force a loader to be assigned to a forest in any period in which a truck requires one, with Ω a sufficiently large constant. Constraints (4.16) break the symmetry between the days that define a period by having the number of trucks unloaded at any mill always be an increasing function over the days of a given period. We note that we are not truly enforcing this monotonicity, as the days of a period are arbitrary and can be permuted without loss of generality if required. Constraints (4.17) force the loader-to-forest assignment variables to be binary. Finally, constraints (4.18) and (4.19) enforce the non-negativity of the other variables, as well as discretize those that count log-truck routes. We denote by $\mathbb{Z}_{\geq 0}$ and $\mathbb{R}_{\geq 0}$ the sets of non-negative integers and reals, respectively.

We note that, in cases where the truck fleet is homogenous, we will express volumes in truckloads as is more common in LTSP literature. The only necessary change to the model in this case is setting the parameter k_{tl} to be equal to 1. In the model as presented, we do note that the volume loaded at every forest on every route is not explicitly defined. However, this can easily be determined from a feasible solution in a greedy fashion. This is, of course, done to dramatically reduce the size of the formulation.

Finally, in many cases in the Canadian forestry industry, there exist contractual obligations that stipulate what proportion of the harvest at each forest site must be sent to each mill. This problem then has more similarities to classic pickup-and-delivery problems. We can represent this in our mathematical model by duplicating our assortments into a different assortment for every mill that has a demand of that assortment. We then treat each forest site f as a vector of multiple forests $\vec{f} = (f_{m_1}, f_{m_2}, \dots f_{m_k})$ for all mills that the forest must serve, and treat each of these as an individual forest throughout the model that provides the needed quantity of the assortments that correspond to that mill. The only change in the model is to then associate vector $\vec{f}$ with a single vector of loader variables $(L_{\vec{f}p})_{p \in P}$, and replace constraint (4.14) and (4.15) as follows:

$$\sum_{f\in\vec{f}}\sum_{t\in T} v_t \sum_{j\in J} L_{jfi} y_{jpd} \leq L_{\vec{f}p}, \forall\ \vec{f} \in F, p \in P, d \in D_p, i \in I, \tag{4.14b}$$

$$\sum_{f\in\vec{f}}\sum_{t\in T} v_t \sum_{d\in D_p}\sum_{m\in M}\sum_{l\in L} x_{fmlpt} \leq \Omega L_{\vec{f}p}, \forall\ \vec{f} \in F, p \in P. \tag{4.15b}$$

4.4 Methodology

We propose to apply column generation to this problem, similar to the method used by Rix et al. (2011). We must generalize the model to take into account multiple periods, loader synchronization, and several other constraints.

4.4.1 Initial Restricted Problem

To solve the linear relaxation of (P) via column generation, we must first determine an initial set of columns J' that makes the problem feasible. As this may be very difficult, we propose to relax the constraints (4.13) and (4.14) associated with loader synchronization, and penalize any violation in the objective function. With these constraints relaxed, the most intuitive and simple route subset of J that guarantees to make the problem feasible is the set of out-and-back routes defined by (f, m, l) for f, m, l in F, M, L, respectively. We repeat this trip as many times as time windows will allow, and add this route as a column for each day of the planning horizon in which this trip is valid for the harvest plan and mill demands of the current period. We denote this restricted master problem (P').

After solving the LP relaxation of (P'), we store the dual values associated with constraints (4.7), (4.8), (4.13), (4.14), and (4.16); which we denote π_{fmlp}, λ_{mpdt}, σ^U_{mpdi}, σ^L_{fpdi}, and γ_{pd}, respectively. Our search then begins for negative reduced cost columns with which to enrich the model to improve the objective value of the optimal solution. We propose to find these columns by performing a set of dynamic programming algorithms, one for each day d of each period p, and for each truck class t.

4.4.2 Enriching the Model with Column Generation

To solve these subproblems, we must first construct a space-time network, which we denote $G = (V, A)$, for the given day of the period and truck class. In this space-time network we discretize the time dimension of the day as in the problem definition, letting δ again be the interval length between two consecutive timesteps.

We define the network with vertex set $V = (M \bigcup F) \times I \times \{0, 1\}$, where 0 corresponds to having an empty truck at that location and 1 corresponds to having a loaded truck. The arc set is then $A = A_w \bigcup A_u \bigcup A_l \bigcup A_{ud} \bigcup A_{ld}$ where A_w, A_u, A_l, A_{ud}, and A_{ld} represent waiting, loading, unloading, unloaded driving, and loaded driving arcs, respectively. The cost of each arc c_{uv} is then easily calculated as a function of per hour operating and waiting costs of that truck. However in calculating the reduced cost of a route, we modify these arc costs as follows, letting $\underline{i}_{uv}$ and $\bar{i}_{uv}$ denote the first and last time intervals over which the arc intersects:

$$c_{uv} \leftarrow \begin{cases} c_{uv} & (u,v) \in A_w, \\ c_{uv} - \sum_{i=\underline{i}_{uv}}^{\bar{i}_{uv}} \sigma^U_{mpdi} & (u,v) \in A_u, \\ c_{uv} - \sum_{i=\underline{i}_{uv}}^{\bar{i}_{uv}} \sigma^U_{fpdi} & (u,v) \in A_l, \\ c_{uv} & (u,v) \in A_{ud}, \\ \min_{l \in L} \{\delta d(f,m) c_{uv} - k_{tl} \pi fmlp\} & (u,v) \in A_{ld}. \end{cases}$$

Any feasible route can then be expressed as a path in this network between any two vertices representing (unloaded) home mill m at different times in the day. The reduced cost of this route will then be equal to the cost of the path minus the dual value sum $\lambda_{mpdt} + \gamma_{pd} - \gamma_{p,d+1}$, which measures a fixed reduced cost associated with operating that truck that day.

We note that this network has a clear topological ordering, which is a chronological ordering with ties broken arbitrarily. To find negative reduced cost routes to add to the master problem, we can therefore utilize a standard label setting algorithm (Cormen et al., 1990, Sec 24.2), in which we associate with each vertex v a label $[pred_v, RC_v]$ which denotes the predecessor of v and the length (reduced cost) of the shortest path to v. For any day d of period p, truck class t and mill m, we provide the algorithm in Figure 4.1. Lines 1 through 6 initialize the labels. Lines 7 through 11 push through the graph and update labels as required. Lines 12 through 15 store all negative reduced cost routes originating and terminating at mill m.

Thus at every master iteration, we store the dual values of constraints (4.7), (4.8), (4.13), (4.14), and (4.16); then solve $|M||T| \sum_{p \in P} |D_p|$ subproblems. All negative reduced cost routes are stored and the columns are added to the master problem. We iterate through this process until no negative reduced cost routes remain or another stopping criteria (such as a time or column limit) is reached.

```
for all v in V do
    pred_v ← null
    if v corresponds to mill m then
        RC_v ← −λ_mpdt − γ_pd + γ_p,d+1
    else
        RC_v ← ∞
for all u in V following the topological ordering do
    for all (u, v) in A do
        if RC_v < RC_u + c_uv then
            RC_v ← RC_u + c_uv
            pred_v ← u
for all v in V do
    if v corresponds to mill m then
        if RC_v < 0 then
            Iterate backwards and store path to v.
```

Figure 4.1 Shortest Path Algorithm for Routing and Scheduling Subproblem

4.4.3 Column Pool Management

At each iteration, upon the resolution of all subproblems, the most general method would be to add all negative reduced cost columns found to the LP. However many of these routes will prove unnecessary and remain non-basic until the algorithm terminates. Therefore we utilize two methods to control the size of the column pool. First, at each iteration we simply added the best (most negative reduced cost) 200 columns found. Second, for each column, we track the number of iterations for which it has been non-basic. Once a column has been inactive for 30 iterations, we delete this column from the pool and model.

4.4.4 Generating an Integer Solution

We then restore integrality to the variables y and T and re-enforce the synchronization constraints as hard constraints to generate a fully feasible solution. We then solve the resulting MILP model with the current column pool of routes via branch-and-bound to get an integer-feasible solution to the problem. We note that this method does not solve the original model fully to optimality, except in the rare case that the optimal solution to the LP is integer feasible. This would require the use of a branch-and-price algorithm (Barnhart et al., 1998). However, solving the linear relaxation to optimality does yield a lower bound with which to compare the best found integer feasible solution to.

4.5 Case Studies

This project was motivated by several case studies provided by FPInnovations, a Canadian not-for-profit organization which carries out scientific research and technology transfer for the Canadian forest industry. Four different case studies, three from Quebec and one from British Columbia, with an annual planning horizon were provided, and we will denote these $A1$ through $A4$. All four studies have a yearly planning horizon partitioned into 26 periods of 14 days. Two classes of truck are available to transport the wood. The smaller class of truck is equipped with its own crane for loading wood. They are usually only used for cleaning up smaller piles of wood to avoid the need to operate a loader at a forest site, as they are less cost efficient per cubic meter of wood to operate (with roughly one third of the carrying capacity) and generally are slower to load. Data sets $A2$ and $A3$ have very inconsistent harvest schedules and hence the schedule balancing constraints (4.10) and (4.11) could not be added while still allowing a mathematically feasible model; however, these were included for data sets $A1$ and $A4$.

We additionally were provided two weekly instances which we denote $W1$ and $W2$. We partitioned the week into 7 periods of a single day. The company that provided these instances only utilized a single truck class, not equipped with an onboard loader. In these weekly instances, the scheduling constraints (4.10) and (4.11), and the wood freshness constraints (4.6) were not relevant to the model.

For each data set, we provide in Table 4.1 the number of forest sites ($|F|$), mills ($|M|$), log assortments ($|L|$), and the total volume of wood harvested across all forests over the planning horizon (V, in m^3). Distances between forests and mills in all data sets ranged from 1 to 6 hours.

Table 4.1 Description of Case Studies

Instance	$\|F\|$	$\|M\|$	$\|L\|$	V
W1	6	5	3	29,745
W2	6	5	3	16,065
A1	43	7	5	722,531
A2	8	1	1	372,670
A3	8	1	2	462,272
A4	3	1	3	743,600

4.6 Experimental Results

As loading and unloading times were 40 minutes in all cases, the most intuitive discretization step to use when modeling the problem was 40 minutes; hence loading and unloading operations took a duration of 1 timestep, and a day had a time dimension of size 36. We implemented the algorithms in C++, and used Gurobi Optimizer 4.6 (Gurobi Optimization) as an LP and MILP solver. All Gurobi parameters were set to defaults except, during the column generation phase of the algorithm, we solved the linear programs using the barrier optimizer to generate interior solutions and hence yield more useful dual values to take to the subproblems. All experimentation was done on an Intel Core i7, 2.67 GHz processor with 4.0 GB of memory.

We solved each of the annual case studies varying the parameters n_p^L that represent the maximum number of sites opened for loading, which we held constant across all periods, from 0 (in which case strictly self-loading trucks could be utilized) up to a maximum based on the size of the data set, after which the number of loaders did not further constrain the instance. Additionally, we varied the parameter ϵ to control schedule balancing through parameters ∞ (no balancing), 0.5, and 0.25 on the relevant instances. All runtimes were limited to 60 minutes, with 30 minutes devoted to column generation and any remaining time devoted to solving the MILP. In Table 4.2 we display the total size of the route pool after stopping the column generation, the total number of variables and constraints in the MILP, the objective value of the best feasible solution (if one was determined), the optimality gap (if the LP was solved to optimality), and the computation time.

It is clear that the existence of a heterogeneous truck fleet adds an additional level of complexity to this problem. When the number of loaders is sufficiently small or large, generating high quality solutions becomes a significantly easier task as the subproblems generate nearly exclusively trucks from a single class. When this is not the case, solutions took longer to find, and in a few cases a feasible solution could not be found under the imposed time constraint. Looking at case study $A4$ specifically, which has the largest volume, the problem is most difficult to solve when one loader is present, and the final gaps are quite large. This enlarged solution space (from requiring both classes of truck) doesn't allow us to find a good feasible solution under the given time constraints. Additionally, more tightly constraining the balanced schedule requirement has an effect on performance.

For the annual case studies, we provide a breakdown of the distribution of the four objective component costs in Figure 4.2. We note that as the routing costs are the most significant, it further motivates taking these costs into account during tactical planning. Storage costs are also quite large in magnitude but with supply and demand both deterministic, there is

Table 4.2 Experimental Results

n_p^L	ϵ	$\|J\|$	Vars	Cons	Objective	Gap	Time (s)
A1							
0	∞	4,891	596,614	533,555	13,625,183	0.61%	697
0	0.5	7,213	629,122	534,284	13,627,674	0.50%	968
0	0.25	8,043	640,742	534,284	13,648,664	0.60%	951
2	∞	8,620	648,840	533,555	9,655,621	6.58%	3600
2	0.5	7,493	633,042	534,284	$---$	$---$	3600
2	0.25	8,350	645,040	534,284	$---$	$---$	3600
4	∞	7,172	628,548	533,555	8,365,557	2.15%	3600
4	0.5	7,767	636,878	534,284	$---$	$---$	3600
4	0.25	8,397	645,698	534,284	8,389,367	2.03%	3600
6	∞	7,724	636,276	533,555	8,303,164	1.40%	3600
6	0.5	8,152	642,268	534,284	8,317,962	$---$	3600
6	0.25	7,825	637,690	534,284	8,326,780	$---$	3600
8	∞	7,660	635,380	533,555	8,293,451	1.28%	3600
8	0.5	8,211	643,094	534,284	8,308,366	1.26%	3600
8	0.25	9,225	657,290	534,284	8,328,978	1.30%	3600
A2							
0	∞	2,078	205,945	264,865	9,682,963	0.09%	33
1	∞	1,192	193,541	264,865	4,260,043	1.90%	73
2	∞	809	188,179	264,865	4,140,578	0.65%	47
A3							
0	∞	1,415	207,407	280,870	10,202,636	0.11%	32
1	∞	1,846	213,441	280,870	6,596,209	6.85%	120
2	∞	1,102	203,025	280,870	6,017,224	0.50%	47
A4							
0	∞	1,268	202,806	277,129	7,059,439	0.18%	12
0	0.5	1,455	205,426	277,858	7,084,142	0.48%	33
0	0.25	1,301	203,270	277,858	7,072,485	0.27%	33
1	∞	1,381	204,388	277,129	4,447,259	18.24%	3600
1	0.5	2,502	220,084	277,858	4,088,901	8.56%	2832
1	0.25	2,409	218,782	277,858	4,234,101	12.11%	3600
2	∞	868	197,206	277,129	3,791,177	0.80%	297
2	0.5	1,383	204,418	277,858	3,793,560	0.76%	472
2	0.25	1,325	203,606	277,858	3,823,025	1.45%	3600
3	∞	896	197,598	277,129	3,786,397	0.22%	81
3	0.5	1,344	203,872	277,858	3,795,472	0.68%	69
3	0.25	1,278	202,948	277,858	3,962,911	4.55%	3600

not as much flexibility to minimize these costs.

For the case study $A1$, storage costs (\$0.5 per cubic meter at the mill and \$0.2 per cubic meter at the forest roadside) accounted for approximately \$2 million, or between roughly 15 to 25 percent of the objective value. We provide in Figure 4.3 the inventory (cumulatively over all log assortments) over time at each mill, and cumulatively at all forest roadsides. We note a high variance over the planning horizon, and smoothing this has been identified as a priority for future work.

We then assessed the performance of this methodology (*ColGen*) by comparing it to the aforementioned two phase flow based approach (*Flow*) (El Hachemi et al., 2014). In the flow based approach, it was necessary to generalize the methodology slightly in the case of annual plans to account for periods of multiple days by adding an additional index to the flow variables. In order to apply this methodology, the model also needed to be slightly adjusted. We assumed a homogeneous fleet of trucks, not equipped with onboard loaders, and hence made the conversion of all volumes to truckloads. Additionally, it is not possible to apply the schedule balancing constraints to a decomposed approach, so those constraints were not included for this comparison.

For both methodologies, we limited the runtime to 40 minutes on the annual sets and 20 minutes on the weekly sets. In all cases, the column generation was able to solve the linear relaxation to optimality, and find a near-optimal integer solution. We provide in Table 4.3 the optimality gap of this solution, and additionally the improvement of this solution over that provided by the decomposed methodology.

In 5 of 6 cases, the column generation methodology finds an improved solution. Though the improvement is not very significant in several cases, we are able to solve a much more robust problem, and are able to find solutions in examples where a decomposition fails. To illustrate, we consider the instance $A4$. When solving the tactical phase of the model, one must bound the number of pickups that can be made from a forest and deliveries that can be made to a mill due to the limited number of hours a loader can be operational. If this

Table 4.3 Comparison of Methodologies

Instance	Gap	*Colgen* Improvement
W1	0.87%	1.05%
W2	3.53%	−2.42%
A1	0.11%	0.55%
A2	0.28%	8.25%
A3	0.12%	3.43%
A4	0.17%	− − −

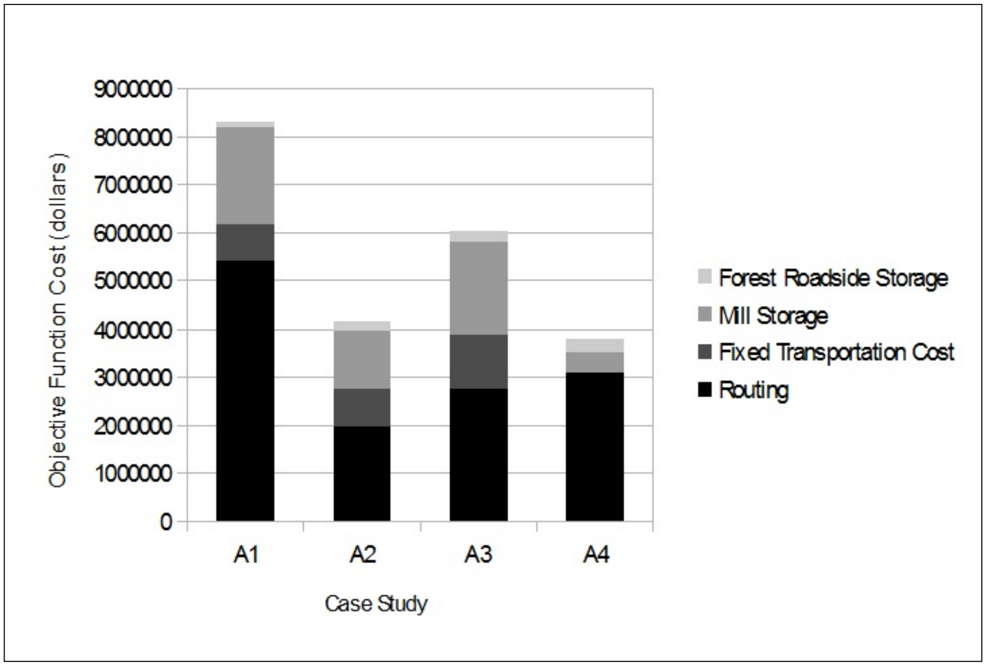

Figure 4.2 Objective function component costs per case study

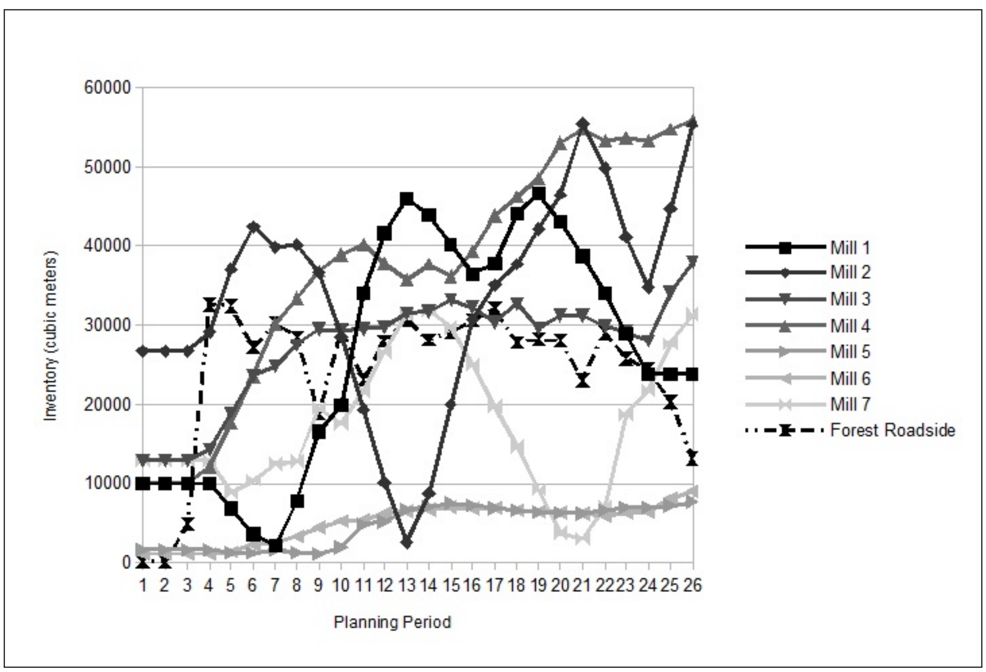

Figure 4.3 Inventory at mills and forest roadside in an industrial problem

expression is constrained too tightly, then the tactical model has the potential to be infeasible. However, if it is not constrained tightly enough, then the resulting tactical solution may yield an infeasible operational subproblem. The existence of different operating hours at different locations only increases the difficulty of these decisions.

4.7 Implementation into Decision Support System

This project was undertaken in collaboration with FPInnovations to develop a complementary tool to the current FPInterface software package. This module of FPSuite is an operational tool used to model the forest supply chain to estimate costs for road construction and maintenence, harvesting, transport and reforestation.

Therefore the goal was to create a decision support system that can be used to formulate a complete plan in a short computational time, with the option to easily modify inputs to perform sensitivity analysis on transportation costs under many different scenarios. Detailed reports must be given in the form of an Excel workbook, allowing the user to track inventories, allocations, and driver and loader schedules throughout the planning horizon, and to easily calculate important key performance indicators such as the average utilization hours of each truck and the ratio of loaded to unloaded travel time. The software developed in this project can be utilized in a stand-alone fashion, or take as inputs the output provided by the FPInterface, to produce these required schedules.

Being able to generate these efficiently and in a simple interface has allowed FPInnovations researchers to independently use this tool in practical settings in order to run scenarios for many Canadian forestry companies. FPInnovations is currently negotiating with several of these companies to pursue the implementation of this optimization tool in their operations.

4.8 Conclusion and Future Work

We have introduced a multi-period tactical wood flow model in which routing and scheduling decisions are incorporated to maximize savings generated from backhaul opportunities and queuing minimization. This problem was modeled as a mixed integer linear program and we solved the linear relaxations via column generation, using dynamic programming to solve the subproblems at each master iteration. Integer feasible solutions were then found via branch-and-bound after solving the linear relaxations to optimality. On problem sets provided by an industrial partner, very good integer feasible solutions were found within a reasonable time limit. The methodology also outperforms a previously developed decomposed approach. We believe that not decomposing the model is justified in many cases, and that column generation is a powerful tool to generate truck schedules.

Future work involves synchronizing the routing decisions with other aspects of the supply chain, such as harvest planning. Additionally, driver specific constraints such as shift length and geographical restrictions have been identified as a priority for future research efforts.

CHAPTER 5

ARTICLE 3: DOCK AND DRIVER SCHEDULING IN A TIMBER TRANSPORT SUPPLY CHAIN

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Chapter Notes

The contents of this chapter were submitted for publication to *Computers & Operations Research* on October 28, 2014. Preliminary work was a winner of the Best Project award in the poster competition at the 4th Value Chain Optimization Summer School, and presented at the following conferences:

- Optimization Days 2014
  - May 2014: Montréal, QC, Canada
- 2nd Annual FIBRE Conference
  - May 2014: Vancouver, BC, Canada
- 56th Annual Conference of the Canadian Operational Research Society
  - June 2014: Ottawa, ONT, Canada
- 4th Value Chain Optimization Summer School
  - June 2014: Halifax, NS, Canada

Abstract

In this article we present a log-truck scheduling problem defined over a multi-week planning horizon. With the goal of moving products from supply points to demand points at minimum cost, this generalizes a classic pickup-and-delivery problem. However unlike most seen in the literature, the formulation in this article manages synchronization constraints between trucks and loading equipment in order to minimize the queuing costs that arise when multiple trucks arrive at a loader at the same time, which is a significant expense to Canadian forestry companies. We derive a mixed integer linear program to represent the problem, in which the key variables are the daily assignment of loaders to forest sites, and the traversal of schedules for each driver that respects loader availability at supply and demand and the driver's own requirements of truck configuration, geographical availability, and shift length and work week requirements. We solve the problem via a branch-and-price heuristic, in which branching is done without backtracking and the subproblem consists of solving a shortest path problem with resource constraints that generates weekly schedules for each driver. We additionally apply interior point stabilization to the resource synchronization constraints linking the trucks to the loaders, a new application of this stabilization technique, which is shown to accelerate the minimization of the objective function. The methodology is tested on several provided industrial case studies.

Keywords: Forestry, pickup-and-delivery problem, synchronization, integer programming, column generation

5.1 Introduction

Canada has approximately 400 million hectares of tree cover, and the Canadian forest sector produced 146.7 million cubic meters of harvest in 2011 (Canadian Council of Forest Ministers). This contributed to 1.1% of national gross domestic product (Natural Resources Canada). In the context of an economy of this scale, small relative reductions in operating costs can yield substantial savings. Additionally, increasing operations efficiency has environmental impacts such as reduction of greenhouse gas emissions. To this end, the use of optimization models and decision support systems is of high importance, and in recent years research initiatives pursuing these models have been highly prioritized.

Transportation costs in particular represent a very significant portion of the total cost of the wood supply chain, with 36% being a reported average in the Canadian context (Audy et al., 2012). This totals a multi-billion dollar expense for the Canadian forest sector. Operational transportation planning involves two types of scheduling that must be synchronized. Driver scheduling is the assignment of shifts to drivers and determining the pickups and deliveries they make on each shift. Dock scheduling is managing these pickups and deliveries at supply and demand points, and giving a schedule to each loader operator, as the majority of trucks do not have onboard cranes and must rely on on-site machinery to load and unload their payload. Most Canadian forest companies have a planner derive these schedules manually, losing significant savings opportunities than can be realized through automated planning.

In addition to saving the decision makers the man hours of creating the schedules, using an optimization methodology can generate several criteria of savings. We note three main phases of transportation planning that are focused on in this paper: allocation, routing, and scheduling. Allocation is the pairing of supply points with demand points over the planning horizon in order to meet demands while minimize hauling distance. Routing is the creation of routes for the trucks that allow us to take advantage of backhaul opportunities in order to minimize unproductive empty driving hours. Finally, scheduling is important in this industry due to truck and driver waiting time when coordinating with loading equipment, which can lead to long queues of trucks if poorly managed. Due to the inherent difficulty, few approaches that exist in literature consider modeling and cumulating these waiting times, despite the significant impact on company operating costs. Additionally, these waiting times when unmanaged in the schedule can yield undelivered loads when shift lengths are finally exceeded for drivers or loader operators, and/or especially costly overtime hours if the company chooses to have them work additional hours beyond the scheduled shift to meet all scheduled deliveries.

Another novel element of the approach developed in this paper is the generation of weekly routes for the drivers rather than daily. This was motivated by industrial problems in which mills are open 24 hours, and some drivers must work overnight shifts that overlap 2 days. There moreover exist situations when mills do have opening and closing hours. However, in order to feasibly deliver all demand, drivers must pick up supply after the mill has closed and return to the mill that evening. He then unloads the delivery upon commencing his next shift when the mill has reopened in the morning. Preliminary resolution attempts showed that daily scheduling could not generate feasible solutions to these problems under the demand constraints laid out, which verifies the current company practice of trucks working and/or resting loaded overnight. Finally, this allows for more direct management of weekly constraints on driver work hours, including differentiating between single shifted and double shifted vehicles.

The focus of this paper will be the multi-period LTSP, with a planning horizon of approximately one month. The key attribute that differs this problem from traditional PDPs and IRPs is the synchronization constraints between the trucks and the loaders that allow for cumulation and minimization of the truck queuing times, a very difficult constraint in practice. We give an MILP formulation based upon a set covering model, develop a branch-and-price heuristic to resolve the problem, and give computational results on several case studies.

In Section 5.2, we give a full description of our problem. In Section 5.3, we present a mathematical formulation, and Section 5.4 gives the details behind the branch-and-price heuristic used to resolve the problem. In Sections 5.5 and 5.6 we discuss the case studies that motivated this problem and the experimental results. Finally, Section 5.7 concludes the paper.

5.2 Problem Definition

The problem we consider in this paper is a multi-period LTSP, with periods defined as weeks in a planning horizon of several weeks. We assume a harvest plan as input, and we solve a routing and scheduling problem for each week for a heterogeneous fleet of log trucks, while managing demand requirements, inventory constraints, and the allocation between supply points (forest sites) and demand points (mills) each week.

This harvest plan is of multiple products differing in terms of species, quality, length and/or diameter. Depending on company practices, the supply managed in this level of scheduling can either be all pre-harvested timber available at the start of the planning horizon, or can become available in a deterministic fashion in future weeks as it is harvested. While these are often anticipated future volumes, advancements in scanning of forest stands make these estimates accurate enough for planning purposes.

We also assume deterministic mill demands over the horizon, though re-optimization may be necessary as demands change over time. The case studies that motivated this research enforce that volumes of supply and demand are approximately equal; this is to avoid creaming of the supply points. If this was not the case, and supply was significantly greater than demand, an optimization model would always choose the supply points that are closest and the average distances would increase over time.

A heterogeneous vehicle fleet is used to deliver the wood. Every vehicle defines a capacity (payload) of each product, which is zero in cases of incompatibility. Different trucks with different capacities implies that volumes must be expressed in a fixed unit of volume (ie m^3), rather than simply truckloads as is common in current literature.

Additionally, every driver has minimum and maximum number of hours, which is defined both per shift and per week, and a minimum resting time between shifts. This definition also allows for double shifted vehicles, in which a vehicle is operated by two drivers in a day in order for higher fleet utilization. This is defined by a minimum number of weekly hours sufficiently high to satisfy both drivers and no mandatory rest time between shifts. Each vehicle is situated at a depot, modeled as a demand point or a garage, which we model as a demand point with zero consumption and inventory capacity. All shifts must start and end at this depot. A truck can be either empty or loaded between shifts; in the latter case it is generally a case of a driver working beyond the operating hours of the mill and leaving the truck loaded in order to unload it in the morning when he returns to work.

Per-hour costs (measured in dollars) are assigned to trucks, one that accounts for when a truck is operating and one that accounts for when it is waiting in queue to use loading equipment. We refer to a pairing of vehicle and driver requirements as a driver schedule.

The management of this fleet differs based on the practices of the forest company. Some employ a set of trucking contractors, which allows for the fleet to be homogenized to a certain degree, whereas others employ independent owner-operator truckers. In either case, a priority position is assigned to each vehicle, and it is important to maximize hours assigned to vehicles that appear higher on the priority list. We choose to incorporate the priority position through truck operating costs, linearly scaled to give high priority trucks a lower cost. The choice was made to enforce the priority positions through costs rather than hard constraints on the number of hours worked in order to guarantee a feasible optimization problem. It is possible that a near-optimal solution generated will give more working hours to a lower priority driver in cases when both routes would be feasible for both drivers; any final solution will be post-processed via a generic sort to always ensure that this is not the case.

At forest sites, we determine the days in which a loader is assigned to load arriving trucks. Each loader can then only move around within this site, movement that is beyond the scope of this model. We place a hard constraint on the number of days in which each forest site can be assigned a loader: this is determined based on the total volume present and hence serves to ensure each loader is being sufficiently utilized in terms of average hours per day. At mills, the loading equipment is permanent and no decisions need to be imposed or costs cumulated. In both situations, the working schedules of the loader operators fix time windows of when trucks can arrive to be served. Whenever a truck must synchronize with a loader at the forest or mill, if the loader is serving another truck then the truck must wait; this yields unproductive labor costs. Loading times can differ based on the equipment available at any location. While a loader can only service one truck at a time, the discretization step length at which we manage the schedules may impose that we model, for example, a 10 minute load time as 2 trucks loaded per 20 minutes.

This LTSP is then to determine the quantity of each product to deliver from each forest to each mill in each week, the necessary inventory between weeks at each forest and each mill, the assignment of routes to log-trucks in order to deliver the produced logs to the mills, and the daily schedule of each loader. Each route defines the day and time of every trucking activity (driving, loading, unloading, waiting), in addition to the start and end of each shift.

5.3 Model Formulation

The MILP formulation consists of input data, decision variables, an objective function, and constraints. The input data appears in Tables 5.1 through 5.3 and the decision variables are listed in Table 5.4.

Constraints

All of the constraints of the formulation are listed in this section.

Inventory

Constraints (5.1) fix the initial inventories at every node. Constraints (5.2) impose the maxima at each demand node each period.

$$w_{nk1} = i_{nk}, \forall n \in N, \tag{5.1}$$

$$\sum_{k \in K} w_{nkp} \leq i_n^{max}, \forall n \in N, p \in P. \tag{5.2}$$

Table 5.1 Input Sets

Notation	Representation
$P = \{1, 2, \ldots, \lvert P\rvert\}$	Set of planning periods
$P' = \{1, 2, \ldots, \lvert P\rvert + 1\}$	Set of planning periods including dummy period for end of horizon
D_p	Set of days in period p
$D = \bigcup_{p\in P} D_p$	Set of days in the planning horizon
I_d	Discretized time dimension of day d
$I_p = \bigcup_{d\in D_p} I_d$	Discretized time dimension of period p
N^{out}	Set of supply nodes
N^{in}	Set of demand nodes
$N = N^{out} \cup N^{in}$	Set of nodes
K	Set of products
T	Set of driver schedules
$depot^t \in N^{in}$	Depot node for schedule t
Θ_t	Set of feasible routes for schedule t
$\Theta = \bigcup_{t\in T} \Theta_t$	Set of routes

Table 5.2 Input Data

Notation	Representation
v_{nkp}	Volume of product k produced at supply node n in period p
d_{nkp}	Demand of product k at demand node n in period p
i_{nk}	Initial inventory of product k at node n
i_n^{max}	Maximum capacity at node n
n_{tp}	Number of trucks available for schedule t in period p
c_{tk}	Capacity of product k on truck used in schedule t
$\rho_{\theta n_1 n_2 k}$	Number of trips on route θ carrying product k from supply node n_1 to demand node n_2
n_d	Number of loaders available on day d
c_{ni}	Loader capacity at node n at time i
$L_{\theta ni}$	Binary parameter indicating if route θ uses loader at node n at time i

Table 5.3 Costs and Penalties

Notation	Representation
$\gamma_t^{transport}$	Per hour cost of operating (driving, loading, unloading) truck on schedule t
$\gamma_t^{waiting}$	Per hour cost of waiting on schedule t
γ_θ^{route}	Total cost of route θ
$\gamma_{nkp}^{shortage}$	Cost per m^3 of missed demand of k at demand node n in p

Table 5.4 Variables

Notation	Representation
$x_{n_1n_2kpt} \in \mathbb{R}_{\geq 0}$	Volume of flow of product k from supply node n_1 to demand node n_2 in period p on schedule t
$w_{nkp} \in \mathbb{R}_{\geq 0}$	Volume of product k stored at node n entering period p in P'
$\hat{d}_{nkp} \in \mathbb{R}_{\geq 0}$	Missed demand at demand node n of product k in period p
$L_{nd} \in \{0,1\}$	Equals 1 if loader is assigned to supply node n on day d
$q_{\theta p} \in \mathbb{Z}_{\geq 0}$	Number of times route θ is traversed in period p

Flow Conservation

Constraints (5.3) and (5.4) are flow conservation constraints at supply and demand nodes, respectively.

$$w_{n_1kp} + \sum_{n_2 \in N^{in}} \sum_{t \in T} x_{n_1n_2kpt} + v_{nkp} = w_{n_1k(p+1)}, \qquad \forall n_1 \in N^{out}, k \in K, p \in P, \tag{5.3}$$

$$w_{n_2kp} + \sum_{n_1 \in N^{out}} \sum_{t \in T} x_{n_1n_2kpt} - d_{n_2kp} + \hat{d}_{n_2kp} = w_{rkl(p+1)}, \qquad \forall n_2 \in N^{in}, k \in K, p \in P. \tag{5.4}$$

Transportation

Constraints (5.5) bound the routes traversed by the number of trucks available.

$$\sum_{\theta \in \Theta_t} q_{\theta p} \leq n_{\theta p}, \forall t \in T, p \in P. \tag{5.5}$$

Constraints (5.6) are set covering constraints that bound the total wood flow between any two points by the capacities of the trucks traversing that path.

$$x_{n_1n_2kpt} \leq \sum_{theta \in \Theta_t} \rho_{\theta n_1 n_2 k} c_{tk} q_{\theta p} \qquad \forall n_1 \in N^{out}, n_2 \in N^{in}, k \in K, p \in P, t \in T \tag{5.6}$$

Constraints (5.7) and (5.8) enforce the loading capacity at each demand and supply point, respectively. Constraints (5.9) restrict the number of days a supply point can be open via loader assignment, and constraints (5.10) bound the total number of supply points open on any given day.

$$\sum_{\theta \in \Theta} L_{\theta ni} q_{\theta p} \leq c_{nd}, \forall n \in N^{in}, d \in D, i \in I_d, \tag{5.7}$$

$$\sum_{\theta \in \Theta} L_{\theta ni} q_{\theta p} \leq c_{nd} L_{nd}, \forall n \in N^{out}, d \in D, i \in I_d, \tag{5.8}$$

$$\sum_{d \in D} L_{nd} \leq n_{nd}, \forall n \in N^{out} \tag{5.9}$$

$$\sum_{n \in N} \sum_{d \in D} L_{nd} \leq n_d. \tag{5.10}$$

Objective Function

Our objective function contains 2 components that contribute to the total cost of a solution: transportation costs and missed demand costs. We mention that the first requirement for a schedule is to meet all demand, and this is modeled as a variable with high penalty for feasibility purposes. The complete mathematical formulation of the model, which we denote as problem (P), is then the minimization of the objective function

$$Z = \sum_{\theta \in \Theta} \gamma_{\theta}^{route} q_{\theta p} + \sum_{n \in N^{in}} \sum_{k \in K} \sum_{p \in P'} \gamma_{nkp}^{shortage} \hat{d}_{nkp}$$

subject to constraints (5.1) through (5.10).

5.4 Methodology

The biggest obstacle in formulating the problem in a set covering formulation is the exponential number of variables representing log-truck routes. Hence we use a branch-and-price based methodology in which we start with an empty pool of routes and generate improving ones a priori. The column generation procedure to generate routes utilizes a DP subproblem, and an integer feasible solution is found by branching in two phases: first on loader variables L_{nd}, and second on route variables $q_{\theta p}$.

5.4.1 Initial Restricted Problem

We first relax the problem (P) to an LP, with the route set Θ initially empty. This restricted master problem is denoted (P'). After resolving (P'), we retrieve the optimal dual solution. Following this, we must determine negative reduced cost columns with which to enrich the model to improve the objective value of the optimal solution. We propose to find these columns by performing a set of dynamic programming algorithms: one for each period p and driver schedule t.

5.4.2 Enriching the Model with Column Generation

To solve these subproblems, we must first construct a space-time network, which we denote $G_{tp} = (V_{tp}, A_{tp})$, for the given schedule and period. This is defined over the nodes of N^{in} and N^{out}, with the depot of the schedule duplicated as rest node r to denote a truck sitting unused between driver shifts.

We define the space-time network with vertex set

$$V_{tp} = source \bigcup sink \bigcup ((N^{in} \bigcup N^{out} \bigcup \{r\}) \times \{0,1\} \times I_p),$$

where $\{0,1\}$ represents the truck empty (0) or loaded (1). For a node $n \in N$, we denote by n_{eik} the node of V_{tp} where $e \in \{0,1\}$ and $i \in I_p$. Arcs are added to the graph which represent every trucking activity, including beginning and ending each shift of the week. The arc set is then the union of the sets listed in Table 5.5. There is significant pre-processing of this arc set to remove arcs that do not correlate with the geographical or temporal availability of the trucker, time windows at loaders, or a product in common with which to link supply and demand. We assume without loss of generality that all waiting is done at demand points, as there are generally less than there are supply.

The cost c_a of each arc a is then easily calculated as a function of per hour operating or waiting costs of that truck multiplied by the distance of the arc. However in calculating the reduced cost RC_a, we translate the cost by subtracting the dual value of the constraint associated with that activity. The applicable constraint appears in Table 5.5. We mention the special case of loaded driving, in which we associate with each arc the product k that maximizes the dual value, and hence minimizes the reduced cost. Any feasible route can then be expressed as a source-to-sink path in this network, with the reduced cost of this route

Table 5.5 Arc Set for Weekly Subproblem

Notation	Activity	Tail	Head	Distance $(i_2 - i_1)$	Constraint
A_{source}	Week commences	$source$	$depot^t_{0i_2}$	0	(5.5)
A_{sink}	Week terminates	$depot^t_{0i_1}$	$sink$	0	none
A_{ld}	Loaded driving	$n^{out}_{1i_1}$	$n^{in}_{1i_2}$	driving time	(5.6)
A_{ud}	Unloaded driving	$n^{in}_{0i_1}$	$n^{out}_{0i_2}, depot_{0i_2}$	driving time	none
A_l	Loading	$n^{out}_{0i_1}$	$n^{out}_{1i_2}$	loading time	(5.8)
A_u	Unloading	$n^{in}_{1i_1}$	$n^{in}_{0i_2}$	unloading time	(5.7)
A_w	Waiting	$n^{in}_{ei_1}$	$n^{in}_{ei_2}$	1	none
A_{st}	Shift end	$depot^t_{ei_1}$	r_{ei_2}	minimum rest time	none
A_r	Rest continues	r_{ei_1}	r_{ei_2}	1	none
A_{sc}	Shift commences	r_{ei_1}	$depot^t_{ei_2}$	0	none

equal to the sum of arc reduced costs.

This network has a clear topological ordering, which is a chronological ordering with ties broken arbitrarily and rest nodes preceding working nodes. To find negative reduced cost routes to add to the master problem, we utilize a label correcting algorithm to solve a SPPRC (Cormen et al., 1990), though we must extend a standard shortest path algorithm to account for multiple shifts in one route. We associate with each node n a vector of labels $[pred_n^i, RC_n^i]$, in which the index i ranges from 0 to the maximum driver shift length. A label then denotes the predecessor node of n and the length (reduced cost) of the shortest path to n, such that the duration of the current shift up to n is i. All nodes only hold one label vector at any time, except the sink node which holds a set Υ of label vectors that holds all paths of negative reduced cost. The details of the algorithm are given in Figure 5.1, where we let V_{tp}^{rest} and V_{tp}^{shift} be the intuitive partition of the node set.

Thus at every master iteration we store the dual values of the necessary constraints, and then solve $|T||P|$ subproblems. All negative reduced cost routes are stored and the columns are added to the master problem. We iterate through this process until no negative reduced cost routes remain (in which case the LP is solved to optimality) or another stopping criteria (such as a time limit) is achieved.

5.4.3 Column Pool Management

At each iteration, the most general method would be to solve every subproblem, and add every negative reduced cost route to the LP. However many of these routes will prove unnecessary and remain non-basic until the algorithm terminates. Therefore we only solve one subproblem for a randomly selected period and driver schedule at each iteration in order to reduce computation time and limit the number of routes generated. Of these generated routes, we then only add the best (most negative reduced cost) 200 found.

At any point of the problem resolution, upon passing a predetermined upper limit on pool size, columns are eliminated randomly until a lower limit is achieved. This lower limit is set to 70% of the upper limit.

5.4.4 Interior Point Stabilization

Any column generation procedure is heavily dependent on the marginal costs (dual values) to guide the search of the subproblem. However these values may be poorly estimated, especially early in the search, due to the linear relaxation being degenerate. When this is the case, the dual problem has an infinite number of optimal solutions. Neame (1999) provides a detailed discussion on this topic. If an extreme point of the dual polyhedron is returned, as is

for all n in V_{tp} **do**
  $pred_n \leftarrow null$
  $RC_n \leftarrow \infty$
$RC_{source} = 0$
for all n_1 in V_{tp} following the topological ordering **do**
  if $n_1 = source$ or $n_1 \in V_{tp}^{rest}$ **then**
    for all (n_1, n_2) in A_{tp} **do**
      if $RC_{n_1}^0 + c_{n_1 n_2} < RC_{n_2}^0$ **then**
        $pred_{n2}^0 \leftarrow (n_1, 0)$
        $RC_{n_2}^0 \leftarrow RC_{n_1}^0 + c_{n_1 n_2}$
  else
    for all (n_1, n_2) in A_{tp} **do**
      for all $m = 0, 1, \ldots, \overline{h}^t$ **do**
        if $m + d_{n_1 n_2} \leq \overline{h}^t$ **then**
          if $n_2 = sink$ **and** $m \geq \underline{h}^t$ **and** $RC_{n_1} + c_{n_1 n_2} < 0$ **then**
            Iterate backwards and store current source-sink path in route pool
          if $n_2 \in V_{tp}^{rest}$ **and** $m \geq \underline{h}^t$ **and** $RC_{n_1}^m + c_{n_1 n_2} < RC_{n_2}^0$ **then**
            $pred_{n2}^0 \leftarrow (n_1, m)$
            $RC_{n_2}^0 \leftarrow RC_{n_1}^m + c_{n_1 n_2}$
          if $n_2 \in V_{tp}^{shift}$ **and** $RC_{n_1}^m + c_{n_1 n_2} < RC_{n_2}^0$ **then**
            $pred_{n2}^{m+d_{n_1 n_2}} \leftarrow (n_1, m)$
            $RC_{n_2}^{m+d_{n_1 n_2}} \leftarrow RC_{n_1}^m + c_{n_1 n_2}$

Figure 5.1 Shortest Path Algorithm for Weekly Routing and Scheduling Subproblem common when retrieving dual values in most LP solvers, this will yield very large dual values for some constraints and values of zero for others. Regarding constraints (5.7), this means a very high penalty for visiting some occupied loaders and no penalty for visiting others.

We thus utilize the IPS technique of Rousseau et al. (2007) to accelerate the column generation procedure. This technique will allow for, at each LP iteration, the generation of a dual solution in the interior of the convex hull of optimal dual solutions. This is done by generating several extreme points of the optimal dual polyhedron and computing an interior point via a convex combination of these extreme points.

We note that in Rousseau et al. (2007), IPS is applied to the set covering constraints of a VRPTW formulation. That is, these constraints are of the form $\sum a_{\theta i} q_\theta \geq 1$, as opposed to the less-than-or-equal constraints (5.7). Therefore the technique must be modified by fixing the right hand side of constraints (5.7) to randomly generated u_{id} if the constraint is tight and ∞ otherwise. At each iteration of the column generation, we solve the master problem several times for varying values of u_{id} randomly chosen between c_{ni} and $c_{ni} + 1$. We then carry to the subproblem the dual values that are the average of all calculated duals of these constraints.

5.4.5 Heuristic Branch-and-Price

In order to solve our problem to optimality, we would have to embed our column generation procedure into a branch-and-bound tree (Barnhart et al., 1998). However we choose to more quickly find integer feasible solutions through the use of an efficient heuristic branching method motivated by Prescott-Gagnon et al. (2009).

We impose branching decisions in two phases. In the first phase we branch on the loader variables L_{nd}, and in the second on route variables $q_{\theta p}$. The reasoning for this sequencing is that the constraints (5.9) and (5.10) are difficult to manage when fixing vehicle routes, so we let the determinations of the loader assignments determine the routing in the second phase. In both phases, we fix the variable with the largest fractional value to 1 upon the resolution of an LP. We do not fix variables to 0 as this does not significantly modify the problem. Moreover we do not allow backtracking; branching decisions can not be reversed. We continue this process until none of these variables that remain unfixed remain with value greater than a parameter ψ in $[0, 1]$.

Branching decisions can have significant impact on further iterations of the methodology. Every time a variable L_{nd} is set to 1, we check if constraints (5.9) or (5.10) are made tight. If so, every variable that is implicitly set to 0 has the associated supply point and day removed from future subproblems. When a variable $q_{\theta p}$ is set to 1, any loader arc that is utilized is then erased from future subproblems. Additionally, if constraint (5.5) is made tight, then all vehicles from that schedule are fully utilized in the given week, and that specific subproblem can be removed from the methodology. After branching in either phase, we iterate through the current route pool and remove any that were made to be infeasible.

To terminate the algorithm and generate an integer-feasible solution after a time limit is elapsed, we enforce integrality constraints on all remaining variables that are integral in the MIP formulation, and solve the resulting problem using branch-and-bound.

5.5 Case Studies

FPInnovations in collaboration with four different partner companies based across Canada provided operational data, of which six instances of approximately 1 month in duration were generated. The first five instances were in the context of hauling roundwood, whereas the final instance represented a problem in chip transportation. In this final instance, as the supply is located at sawmills, there exist no loader allocation decisions and hence the variables L_{nd} can all be parametrized to the constant value 1. We provide in Table 5.6 the details of each instance.

Under $|D_p|$, we list the ranges of number of days the mill loaders are open, which can vary by mill. Due to the heterogeneous truck fleet, the exact number of truckloads will vary based on the final solution. However for illustrative purposes, we note that the roundwood trucks used in the problems vary from 38 to 56 cubic meters of payload, whereas the chip trucks vary from 20 to 22 BDT (bone dry tons).

Average loaded and empty driving times between all supply and demand points were generated from the forest supply chain control platform FPInterface, developed by FPInnovations. Cycle times ranged between 2 and 8 hours.

Table 5.6 Description of Case Studies

Instance	$\lvert P\rvert$	$\lvert N^{out}\rvert$	$\lvert N^{in}\rvert$	$\lvert K\rvert$	Gross Volume	$\lvert T\rvert$	Trucks	Priority Classes	$\lvert D_p\rvert$
1	3	39	4	3	141456	62	62	62	4-5
2	4	8	4	3	48500	6	21	1	5
3	4	8	4	3	53100	6	21	1	5
4	4	8	4	3	76952	7	32	1	5
5	4	21	3	1	72000	2	30	1	5-7
6	5	5	1	1	32500	6	36	2	4-6

5.6 Experimental Results

The methodology was modeled in Visual Studio (C++), with Gurobi Optimizer 5.6.3 (Gurobi Optimization) used as a solver of the master problem. All parameters were set to the default setting. The discretization step used in all cases was chosen to be 20 minutes, as that is approximately the degree of accuracy to which we can measure driving distances. All experimentation was done on an Intel Core i7, 2.67 GHz processor with 4.0 GB of memory, with a 30 minute limit on runtime. Each instance was solved three times, with results averaged.

As mentioned in Section 5.2, all solutions for case studies 1 and 6 are post-processed to ensure that any higher priority truck is always working more hours than a lower priority truck for which the given schedule is feasible. This is done with a generic sort algorithm.

5.6.1 Sensitivity to Loader Availability

We first wish to analyze the sensitivity of the formulation to the parameters n_{nd} that bound the number of days in which a forest site can be assigned a loader. This parameter is determined prior to optimization by determining the total time required to load all supply on to trucks (based on average truck capacity), and dividing this time by an average daily loader utilization. We iterate this utilization from 3 to 15 hours as in Table 5.7, for all of the roundwood instances.

Several key performance indicators are used to measure solution quality. We give the percentage of total demand attained, and the total number of daily loader assignments made. Additionally, we cumulate the total number of paid transportation hours in the found solution, the total transportation cost measured in dollars per cubic meter, the backhaul savings (expressed as a percentage) compared to the number of driving hours required if each delivery in the optimal solution were traversed in an out-and-back manner, and the percentage of working hours in which the trucks are waiting unproductively.

We see that the quality of the solution obtained is highly sensitive to the loader constraints (5.9), as the percentage of demand satisfied drops to unacceptable levels in 4 out of 5 instances at the maximum parameter setting. However, maximizing the utilization of the loaders is very important based on conversations with forestry experts with respect to the practicality of a solution. We view the quality of the solution obtained for each parameter setting with respect to the demand attainment and backhaul savings in Figures 5.2 and 5.3, respectively.

Relative to the low utilization levels of 3 hours per day, transportation costs rise in these experiments by an average of $\$0.24/m^3$ when increasing the average utilization to 9 hours. Therefore it is likely that to be able to generate feasible (up to measurement error of supply

Table 5.7 Sensitivity to Loader Availability

Instance	Average Loader Utilization	Demand Met (%)	Loader Days	Total Hours	Transportation Cost ($\$/m^3$)	Backhaul Savings (%)	Waiting Time (%)
1	3	100.00	237	12809.33	9.94	1.85	0.46
1	6	100.00	174	12710.00	9.86	1.85	0.59
1	9	99.94	133	12703.00	9.85	1.34	0.86
1	12	100.00	108	12925.67	10.02	0.72	0.87
1	15	99.95	104	13060.00	10.12	0.25	1.14
2	3	100.00	80	3197.00	9.84	4.87	0.79
2	6	100.00	68	3173.33	9.78	4.65	0.57
2	9	99.83	44	3326.00	10.07	1.45	3.46
2	12	86.80	33	2883.67	9.94	1.39	4.94
2	15	75.08	27	2645.67	10.46	0.88	5.96
3	3	99.99	80	3406.67	9.59	3.78	0.60
3	6	99.98	74	3393.33	9.54	4.88	0.76
3	9	100.00	50	3524.67	9.75	3.26	3.06
3	12	83.08	36	2991.33	9.72	1.25	6.72
3	15	52.46	28	1689.67	8.72	1.58	6.19
4	3	98.83	98	5068.33	9.92	9.62	1.12
4	6	98.78	81	5032.67	9.84	9.92	1.41
4	9	96.77	60	5205.67	10.29	5.71	2.79
4	12	96.03	42	5529.67	10.54	4.18	9.14
4	15	85.08	32	5132.00	10.87	1.40	11.37
5	3	99.54	216	6955.33	14.50	1.21	0.61
5	6	99.59	115	7017.33	14.58	0.97	1.07
5	9	100.00	74	7322.67	15.05	1.03	2.05
5	12	94.05	53	7164.33	15.47	0.46	3.75
5	15	71.29	41	5298.00	14.96	0.60	5.10

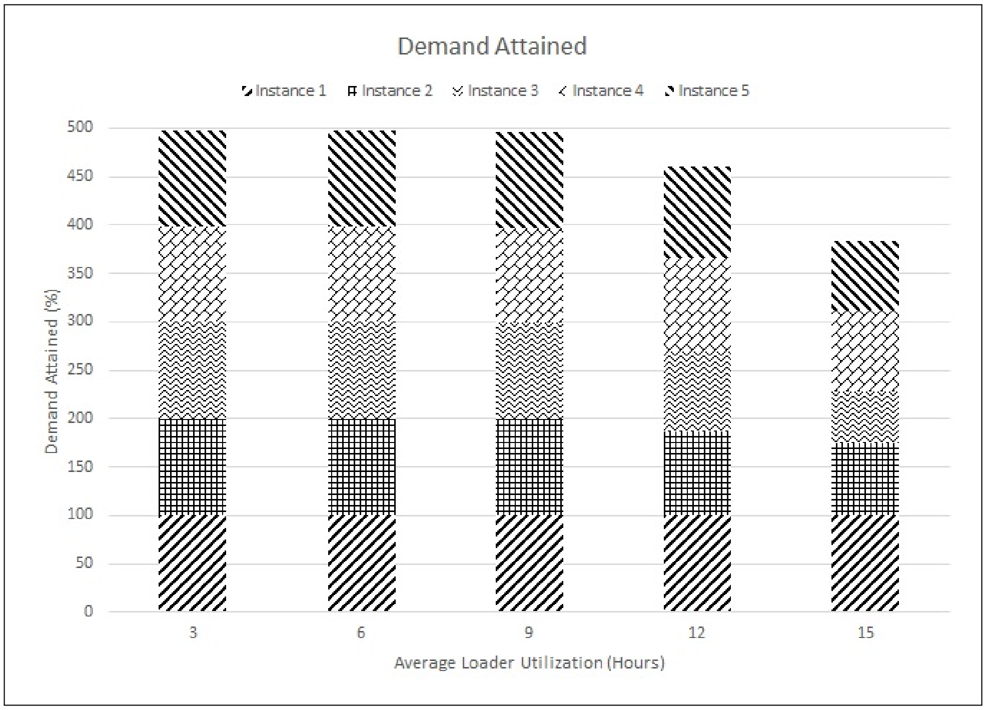

Figure 5.2 Demand Attainment vs Average Loader Utilization

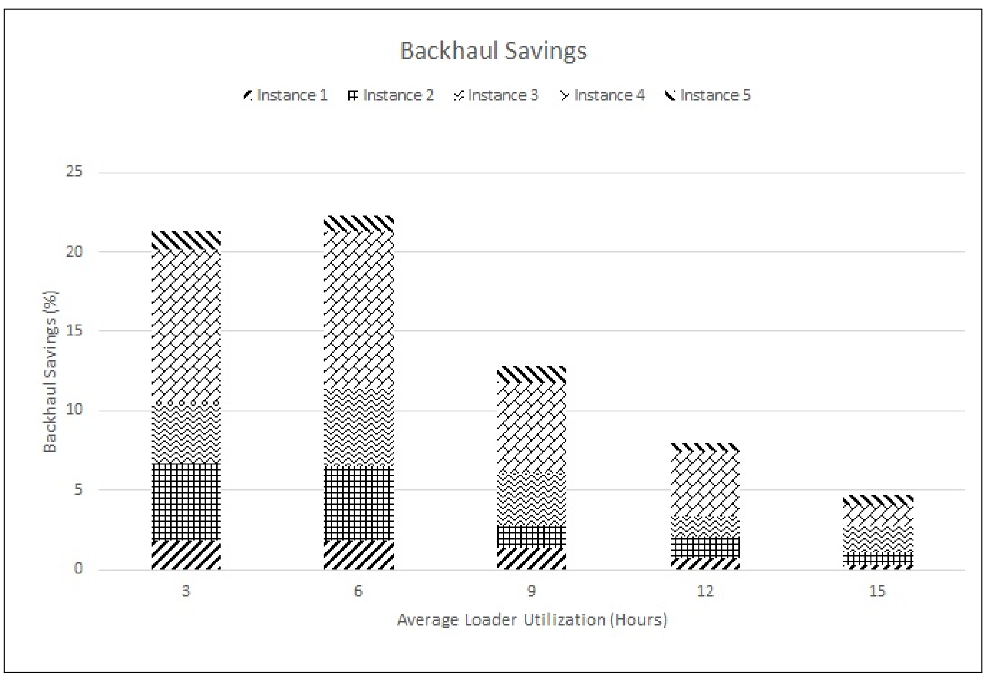

Figure 5.3 Backhaul Savings vs Average Loader Utilization

volumes) solutions while satisfying this significantly higher utilization is worth the marginal increase in transportation costs.

5.6.2 Impact of Interior Point Stabilization

In order to measure the impact of IPS stabilized column generation, we next compare to an unstabilized implementation of the same methodology with dual values retrieved directly from Gurobi after a single LP resolution. For each instance, we give a computational comparison at the setting of parameter values n_{nd} corresponding to a 9 hour utilization. The experimental results appear in Table 5.8, with solution quality measured based upon the same key performance indicators as in Table 5.7.

The stabilized methodology yields a solution with a higher level of demand attainment in all instances except 4, and a less expensive per unit solution in all instances except 2 and 6. On average, volume delivered increases by 1.24% and per unit transportation costs decrease by 2.8% upon the application of IPS.

5.6.3 Comparison with Unsynchronized Resolution

We finally compare to a solution generated modeling the problem as more commonly seen in LTSP literature, where vehicle routes must respect the time windows defined by each loader but the resource synchronization constraints are not enforced in a solution. This serves as a practical lower bound for transportation costs, that is, one that results from optimizing the problem that ignores the costs and schedule feasibility associated with modeling the queuing time of trucks waiting for loaders. In this situation, constraints (5.7) are removed from the formulation and constraints (5.8) have their right hand sides multiplied by a sufficiently large constant (in our case chosen to be the total number of trucks) so that any number of trucks can traverse a loading or unloading arc. The problem is then solved so as to minimize the vehicle routing costs by maximizing the backhaul savings, while still respecting driver schedule constraints and time windows. The methodology used is otherwise the same, except the subproblem network structure does not contain waiting arcs during operating hours of any loader; moreover we do not delete loading or unloading arcs from this subproblem upon branching. Additonally, with no constraints representing synchronization with permanent mill loaders, IPS stabilization is inapplicable.

For each instance, we again give a computational comparison between both methodologies, at the setting of parameter values n_{nd} corresponding to a 9 hour utilization. The experimental results appear in Table 5.8, with solution quality measured based upon the same key performance indicators as in Table 5.7.

Table 5.8 Computational Impact of Synchronization and Interior Point Stabilization

Instance	Synchronization	Stabilization	Demand Met (%)	Loader Days	Total Hours	Transportation Cost ($\$/m^3$, \$/BDT)	Backhaul Savings (%)	Waiting Time (%)
1	N	N	100.00	114	12062.67	9.38	2.09	0.03
1	Y	Y	99.94	133	12703.00	9.85	1.34	0.86
1	Y	N	98.25	134	12849.00	10.13	0.65	1.07
2	N	N	99.88	43	3110.67	9.63	3.92	0.00
2	Y	Y	99.83	44	3326.00	10.07	1.45	3.46
2	Y	N	95.87	43	3188.67	10.04	0.76	3.67
3	N	N	99.98	48	3331.00	9.41	4.04	0.00
3	Y	Y	100.00	50	3524.67	9.75	3.26	3.06
3	Y	N	97.60	47	3624.67	10.20	1.26	4.21
4	N	N	99.98	54	5095.67	9.93	12.10	0.01
4	Y	Y	96.77	60	5205.67	10.29	5.71	2.79
4	Y	N	97.63	55	5577.67	10.82	5.46	4.31
5	N	N	100.00	62	6703.33	13.96	0.67	0.08
5	Y	Y	100.00	74	7322.67	15.05	1.03	2.05
5	Y	N	100.00	76	7674.00	15.78	1.00	1.93
6	N	N	100.00	-	11655.00	37.67	0.00	0.01
6	Y	Y	99.82	-	11782.00	38.01	0.00	1.78
6	Y	N	99.59	-	11725.00	37.91	0.00	1.63

It is clear that the unsynchronized methodology returns a less expensive solution, delivering an average of 0.58% more demand at a 3.7% lesser cost in dollars per cubic meter (bone dry ton). This results from a more focused maximization of the backhaul opportunities without respect for the synchronization constraints, though of course there exist no backhauls in the single-sink chip transportation instance. However this objective value is indeed biased by not cumulating waiting times of trucks while waiting for another truck to (un)load, and the waiting times seen in the synchronized methodology developed in this article have been noted to be much lower than those realized in practice. Hence being able to provide with confidence a schedule that will not have undelivered loads and/or exceeded maximum shift lengths for drivers and loader operators, provides a beneficial scheduling tool to industry decision makers.

5.7 Conclusion and Future Work

In this article, we have considered an LTSP defined over a planning horizon of approximately one month. Unlike most other problems studied in the literature, we enforce synchronization constraints between vehicles and loaders in order to cumulate and minimize driver waiting times in addition to other transportation costs. Additionally, we generate weekly driver schedules in order to manage situations of picking up a load on one day and delivering on another day, which is necessary when drivers work overnight shifts or when they work later than mill closing hours and must unload their truck on the next day's shift. This also allows for more direct management of weekly schedule requirements. We formulate an MILP representation of the problem, which is resolved via a branch-and-price heuristic, with a subproblem of a weekly vehicle routing and scheduling problem. In six industrial case studies, we are able to provide a solution whose cost lies within a reasonable distance to that of schedules generated through optimization without respect for the synchronization constraints. This allows for generation of a schedule without unpredictable future costs and infeasibilities that arise from the lengthy queues of trucks.

Observations from forestry experts have yielded several directions for future research. First, driver waiting times are many times the result of unpredictable elements such as traffic, truck or equipment failure, unavailability of the expected wood, or unscheduled driver breaks. This necessitates a solution approach that emphasizes this inherent stochasticity. Additionally another cost that has been mentioned as significant is the costs associated with moving loaders between forest sites. While limiting the number of days each site can be open over the horizon proved beneficial in this regard, a better approach would be to cumulate the routing costs of the loaders in order to provide more industrially practical solutions.

CHAPTER 6

GENERAL DISCUSSION

In this thesis, we implemented optimization models to decrease transportation costs in the wood procurement supply chain. At different levels of planning, this necessitates the integration of production and inventory planning, vehicle routing and scheduling, and loader scheduling. In current practice, most Canadian companies make these decisions manually, losing significant opportunities for financial savings and a correlated reduction in environmental footprint.

This thesis has provided several contributions to the current literature. From an industrial point of view, perhaps the most novel contribution is that of Chapter 3, as a DSS that combines harvest scheduling and vehicle routing decisions is new to the industry. This is notable as, despite focus in both OR literature and industrial practice on the optimization of backhaul opportunities, their incidence is directly dependent on the location of the supply points at any time. The cost savings realized in this chapter are the most measurably significant of this thesis, though many constraints related to the harvest schedule are not considered. Further research directions would include incorporating vehicle routing constraints into more robust harvest scheduling models.

From a methodological point of view, the literature on VRPs with resource synchronization constraints is very sparse and we have not seen column generation applied to a problem of this form, as we have done in Chapters 4 and 5. Furthermore, the IPS stabilized column generation of Chapter 5 is a supplementary contribution. While its impact when applied to vertex-covering constraints as in the seminal work of Rousseau et al. (2007) is well studied, the modification to these synchronization constraints is an interesting new application with a measurable performance improvement over unstabilized column generation. It would be interesting to consider this in other contexts, though solving the subproblem exactly may become an $\mathcal{NP}$-hard problem if the setting necessitates the generation of cycle-free vehicle routes.

With a forest industry culture known as conservative, especially true in Canada, there have been challenges with implementation of the DSSs developed in this thesis in the industrial setting. Many drivers, for example, are currently paid per load rather than per hour. They moreover do not have fixed start and end times of their shifts, but are rather given a set of pickups and deliveries they are required to make subject only to opening and closing hours. Hence a DSS that assigns shift times and slots for each pickup and delivery requires a large change in practice. Related to this, the minimization of global transportation costs is not always correlated with the preferred solution in practice. If this minimization assigns to a driver a new schedule with fewer trips of longer length, then he will be unlikely to agree. Though this cost savings could be allocated fairly over all actors, another change in practice with respect to payment methods would be necessary.

Additionally, stochasticity present in supply, demand, travel times, and truck and/or loader failure have not been considered in this thesis. In practice, industry decision makers do not have the full knowledge of these model parameters when constructing an initial schedule. Reoptimizing the static instance is generally not a preferred solution to this for several reasons. First, it is very time consuming to both reenter the data and re-solve the problem, while a solution policy must be determined quickly. Second, a secondary objective in this case is to minimize the perturbation to the original plan, so the least number of drivers are affected with a change to their schedule. An interface that allows for heuristic reoptimization is a very important future research direction.

It is also the case in the Canadian context that capacity of a vehicle depends on not only the pairing of vehicle and product, but also on the road traversed, as roads have maximum weight restrictions. Loader movement costs have also been ignored; this has been pointed out by industrial partners as a significant cost that needs to be cumulated in order for implementation to be a realistic goal. The implementation of these aspects are identified as meaningful extensions to this thesis.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

VRPs in forestry differ from more classic applications based on several criteria that necessitate new problem formulations and methodologies. The volumes available at supply points and required at demand points are almost always much greater than truck capacity, so they must be visited more than once. Due to the number of contractors and independent owner-operators that are employed for transportation the vehicle fleet is often highly heterogeneous in terms of capacity of each product, depot location, and driver shift requirements. Additionally, trucks must synchronize with loading equipment at supply and demand points; managing the queues of waiting trucks to minimize these unproductive hours is essential in order to minimize operational costs for the company. For realistic sized instances of these problems, exact methods are generally not practical and hence we developed column generation based matheuristics to resolve several different problem formulations.

In Chapter 3, we generalized a common tactical problem of scheduling harvest teams to forest sites over a year, in order to meet mill demands of multiple harvested products while minimizing wood procurement costs. Unlike other harvest planning models that appear in the literature, we took advantage of the relatively higher flexibility in the harvest sequence in order to facilitate vehicle routing decisions. This allowed for a higher incidence of backhaul opportunities, minimizing empty driving time, while also matching route lengths with the requested shifts of employed trucking contractors over the planning horizon. This is especially important in the Canadian context as demand for drivers is very high in other industries, and guaranteeing these shifts is necessary to retain a permanent fleet. A branch-and-price based heuristic was developed to resolve the problem, with columns representing vehicle routes generated by way of a DP algorithm on a SPPRC. Branching was performed on harvest team decisions. Compared to a decomposed optimization scheme that initially solves the harvest without respecting vehicle routing decisions, we realized a reduction in transportation costs by an average of 12.4%.

In Chapter 4, we assumed the production decisions to be deterministic input over this tactical planning horizon, and solved a vehicle routing and scheduling problem to deliver the timber to the mills. Transportation and inventory costs were minimized, with transportation savings realized through backhaul opportunities and minimization of truck queuing. An MILP formulation was solved with column generation and a DP subproblem, with a final integer-feasible schedule generated with branch-and-bound on the final column pool. This methodology performed favorably with branch-and-bound on an arc flow MILP formulation, finding lower cost solutions in 5 of 6 considered case studies.

In Chapter 5, an operational LTSP with a planning horizon of 4-6 weeks was considered. The problem formulation was similar to that of Chapter 4; however columns represent a weekly driver schedule as opposed to daily. This allowed for direct management of weekly driver shift requirements, as well as managing situations of drivers working overnight shifts or loading a specific shipment on one day's shift and unloading it on the following one. The driver fleet was much more heterogeneous than in the previous problem, with specific shift requirements for each truck and priority positions for each driver that were respected. Loader synchronization constraints were again present, and an MILP was solved with a branch-and-price heuristic. The subproblem was to find a feasible weekly schedule for each driver that meets mill demands at minimum cost. We used a branch-and-price heuristic to resolve the problem, with IPS stabilized column generation and a subproblem of determining the weekly driver schedules. The methodology was tested on several case studies in roundwood and chip transportation, with industrially feasible solutions generated in a reasonable runtime. Compared with an unsynchronized optimization methodology that more accurately reflects the scheduling approach in industrial practice, we realize solutions of a similar planned cost that provide a much higher guarantee of practical feasibility due to the management of truck queuing at the loaders.

As a general conclusion, through our collaboration with FPInnovations we have derived problem formulations that most accurately reflect the needs of companies in the Canadian sector and developed a suite of DSSs for their use. We believe that the use of these contributions can be realized in the sector to signifantly improve their operations efficiency, and hope that we will motivate future research in this field.

REFERENCES

Adulyasak, Y., Cordeau, J.-F., and Jans, R. Formulations and branch-and-cut algorithms for multivehicle production and inventory routing problems. *INFORMS Journal on Computing*, 26(1):103–120, 2013. doi:10.1287/ijoc.2013.0550.

Andersson, G., Flisberg, P., Lidén, B., and Rönnqvist, M. Ruttopt-a decision support system for routing of logging trucks. *Canadian Journal of Forest Research*, 38(7):1784–1796, 2008. doi:10.1139/X08-017.

Audy, J.-F., D'Amours, S., and Rönnqvist, M. Planning methods and decision support systems in vehicle routing problems for timber transportation: A review. Technical Report CIRRELT-2012-38, CIRRELT, July 2012. `https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2012-38.pdf`.

Audy, J.-F., D'Amours, S., Rousseau, L.-M., and Favreau, J. Virtual transportation manager: A decision support system for collaborative forest transportation. Technical Report CIRRELT-2013-34, CIRRELT, May 2013. `https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2013-34.pdf`.

Bajgiran, O., Zanjani, M., and Nourelfath, M. A langrangian relaxation based heuristic for integrated lumber supply chain tactical planning. Technical Report CIRRELT-2014-34, CIRRELT, July 2014. `https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2014-34.pdf`.

Baldacci, R. and Mingozzi, A. A unified exact method for solving different classes of vehicle routing problems. *Mathematical Programming*, 120(2):347–380, 2009. doi:10.1007/s10107-008-0218-9.

Baldacci, R., Christofides, N., and Mingozzi, A. An exact algorithm for the vehicle routing problem based on the set partitioning formulation with additional cuts. *Mathematical Programming*, 115(2):351–385, 2008. doi:10.1007/s10107-007-0178-5.

Baldacci, R., Mingozzi, A., and Roberti, R. Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints. *European Journal of Operational Research*, 218(1):1–6, 2012. doi:10.1016/j.ejor.2011.07.037.

Balinski, M. and Quandt, R. On an integer program for a delivery problem. *Operations Research*, 12(2):300–304, 1964. doi:10.1287/opre.12.2.300.

Bard, J. and Nananukul, N. The integrated production–inventory–distribution–routing problem. *Journal of Scheduling*, 12(3):257–280, 2009. doi:10.1007/s10951-008-0081-9.

Bard, J. and Nananukul, N. A branch-and-price algorithm for an integrated production and inventory routing problem. *Computers & Operations Research*, 37(12):2202–2217, 2010. doi:10.1016/j.cor.2010.03.010.

Barnhart, C., Johnson, E., Nemhauser, G., Savelsbergh, M., and Vance, P. Branch-and-price: column generation for solving huge integer programs. *Operations Research*, 46(3): 316–329, March 1998. doi:10.1287/opre.46.3.316.

Beaudoin, D., LeBel, L., and Frayret, J.-M. Tactical supply chain planning in the forest products industry through optimization and scenario-based analysis. *Canadian Journal of Forest Research*, 37(1):128–140, 2007. doi:10.1139/x11-175.

Beck, S. and Sessions, J. Forest road access decisions for woods chip trailers using ant colony optimization and breakeven analysis. *Croatian Journal of Forest Engineering*, 34(2): 201–215, 2013.

Bell, W., Dalberto, L., Fisher, M., Greenfield, A., Jaikumar, R., Kedia, P., Mack, R., and Prutzman, P. Improving the distribution of industrial gases with an on-line computerized routing and scheduling optimizer. *Interfaces*, 13(6):4–23, 1983. doi:10.1287/inte.13.6.4.

Bent, R. and Van Hentenryck, P. A two-stage hybrid algorithm for pickup and delivery vehicle routing problems with time windows. *Computers & Operations Research*, 33(4): 875–893, 2006. doi:10.1016/j.cor.2004.08.001.

Berbeglia, G., Cordeau, J.-F., Gribkovskaia, I., and Laporte, G. Static pickup and delivery problems: a classification scheme and survey. *TOP*, 15(1):1–31, 2007. doi:10.1007/s11750-007-0009-0.

Bixby, R., Gregory, J., Lustig, I., Marsten, R., and Shanno, D. Very large-scale linear programming: A case study in combining interior point and simplex methods. *Operations Research*, 40(5):885–897, 1992. doi:10.1287/opre.40.5.885.

Bramel, J. and Simchi-Levi, D. A location based heuristic for general routing problems. *Operations Research*, 43(4):649–660, 1995. doi:10.1287/opre.43.4.649.

Bramel, J. and Simchi-Levi, D. On the effectiveness of set covering formulations for the vehicle routing problem with time windows. *Operations Research*, 45(2):295–301, 1997. doi:10.1287/opre.45.2.295.

Bredström, D. and Rönnqvist, M. Combined vehicle routing and scheduling with temporal precedence and synchronization constraints. *European Journal of Operational Research*, 191 (1):19–31, 2008. doi:10.1016/j.ejor.2007.07.033.

Bredström, D., Jönsson, P., and Rönnqvist, M. Annual planning of harvesting resources in the forest industry. *International Transactions in Operational Research*, 17(2):155–177, 2010. doi:10.1111/j.1475-3995.2009.00749.x.

Canadian Council of Forest Ministers. National forestry database. `http://nfdp.ccfm.org/`. Accessed October 13, 2014.

Carlsson, D. and Rönnqvist, M. Backhauling in forest transportation: models, methods, and practical usage. *Canadian Journal of Forest Research*, 37(12):2612–2623, 2007. doi:10.1139/X07-106.

Chandra, P. and Fisher, M. Coordination of production and distribution planning. *European Journal of Operational Research*, 72(3):503–517, 1994. doi:10.1016/0377-2217(94)90419-7.

Chauhan, S., Frayret, J.-M., and LeBel, L. Supply network planning in the forest supply chain with bucking decisions anticipation. *Annals of Operations Research*, 190(1):93–115, 2011. doi:10.1007/s10479-009-0621-5.

Choi, E. and Tcha, D.-W. A column generation approach to the heterogeneous fleet vehicle routing problem. *Computers & Operations Research*, 34(7):2080–2095, 2007. doi:10.1016/j.cor.2005.08.002.

Christiansen, M. and Nygreen, B. Robust inventory ship routing by column generation. In Desaulniers, G., Desrosiers, J., and Solomon, M., editors, *Column generation*, pages 197–224. Springer, 2005. doi:10.1007/0-387-25486-2_7.

Clarke, G. and Wright, J. W. Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research*, 12(4):568–581, 1964. doi:10.1287/opre.12.4.568.

Coelho, L. and Laporte, G. The exact solution of several classes of inventory-routing problems. *Computers & Operations Research*, 40(2):558–565, 2012. doi:10.1016/j.cor.2012.08.012.

Coelho, L., Cordeau, J.-F., and Laporte, G. Thirty years of inventory-routing. *Transportation Science*, 48(1):1–19, 2013. doi:10.1287/trsc.2013.0472.

Cordeau, J.-F. and Laporte, G. The dial-a-ride problem: models and algorithms. *Annals of Operations Research*, 153(1):29–46, 2007. doi:10.1007/s10479-007-0170-8.

Cordeau, J.-F., Gendreau, M., and Laporte, G. A tabu search heuristic for periodic and multi-depot vehicle routing problems. *Networks*, 30(2):105–119, 1997. doi:10.1002/(SICI)1097-0037(199709)30:2<105::AID-NET5>3.0.CO;2-G.

Cordeau, J.-F., Laporte, G., and Mercier, A. A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational Research Society*, 52(8):928–936, 2001.

Cordeau, J.-F., Gendreau, M., Hertz, A., Laporte, G., and Sormany, J.-S. New heuristics for the vehicle routing problem. In Langevin, A. and Riopel, D., editors, *Logistics Systems: Design and Optimization*, pages 279–297. Springer US, 2005. doi:10.1007/0-387-24977-X_9.

Cormen, T., Leiserson, C., Rivest, R., and Stein, C. *Introduction to Algorithms*. The MIT Press, Cambridge, MA, USA, 1990.

D'Amours, S., Rönnqvist, M., and Weintraub, A. Using operational research for supply chain planning in the forest products industry. *INFOR*, 46(4):265–281, 2008. doi:10.3138/infor.46.4.265.

Dantzig, G. and Ramser, J. The truck dispatching problem. *Management Science*, 6(1): 80–91, 1959. doi:10.1287/mnsc.6.1.80.

Dems, A., Rousseau, L.-M., and Frayret, J.-M. Effects of different cut-to-length harvesting structures on the economic value of a wood procurement planning problem. *Annals of Operations Research*, pages 1–22, 2013. doi:10.1007/s10479-013-1336-1.

Desaulniers, G., Desrosiers, J., and Solomon, M. *Column Generation*, volume 5. Springer, New York, NY, USA, 2005.

Desaulniers, G., Lessard, F., and Hadjar, A. Tabu search, partial elementarity, and generalized k-path inequalities for the vehicle routing problem with time windows. *Transportation Science*, 42(3):387–404, 2008. doi:10.1287/trsc.1070.0223.

Desaulniers, G., Rakke, J., and Coelho, L. A branch-price-and-cut algorithm for the inventory-routing problem. Technical Report G-2014-19, GERAD, April 2014. `http://www.gerad.ca/fichiers/cahiers/G-2014-19.pdf`.

Desrochers, M., Desrosiers, J., and Solomon, M. A new optimization algorithm for the vehicle routing problem with time windows. *Operations Research*, 40(2):342–354, 1992. doi:10.1287/opre.40.2.342.

Dorigo, M., Birattari, M., and Stützle, T. Ant colony optimization. *Computational Intelligence Magazine, IEEE*, 1(4):28–39, 2006. doi:10.1109/MCI.2006.329691.

Drexl, M. Synchronization in vehicle routing—a survey of vrps with multiple synchronization constraints. *Transportation Science*, 46(3):297–316, 2012. doi:10.1287/trsc.1110.0400.

Drexl, M. Applications of the vehicle routing problem with trailers and transshipments. *European Journal of Operational Research*, 227(2):275–283, 2013. doi:10.1016/j.ejor.2012.12.015.

Dror, M. and Trudeau, P. Split delivery routing. *Naval Research Logistics (NRL)*, 37(3): 383–402, 1990. doi:10.1002/nav.3800370304.

Dror, M., Laporte, G., and Trudeau, P. Vehicle routing with split deliveries. *Discrete Applied Mathematics*, 50(3):239–254, 1994. doi:10.1016/0166-218X(92)00172-I.

Du Merle, O., Villeneuve, D., Desrosiers, J., and Hansen, P. Stabilized column generation. *Discrete Mathematics*, 194(1):229–237, 1999. doi:10.1016/S0012-365X(98)00213-1.

Ebben, M., Van Der Heijden, M., and Van Harten, A. Dynamic transport scheduling under multiple resource constraints. *European Journal of Operational Research*, 167(2):320–335, 2005. doi:10.1016/j.ejor.2004.03.020.

El Hachemi, N., Gendreau, M., and Rousseau, L.-M. A hybrid constraint programming approach to the log-truck scheduling problem. *Annals of Operations Research*, 184(1):163–178, 2011. doi:10.1007/s10479-010-0698-x.

El Hachemi, N., Gendreau, M., and Rousseau, L.-M. A heuristic to solve the synchronized log-truck scheduling problem. *Computers and Operations Research*, 40(3):666–673, 2013. doi:10.1016/j.cor.2011.02.002.

El Hachemi, N., Hallaoui, I., Gendreau, M., and Rousseau, L.-M. Flow-based integer linear programs to solve the weekly log-truck scheduling problem. *Annals of Operations Research*, pages 1–11, 2014. doi:10.1007/s10479-014-1527-4.

Epstein, R., Morales, M., Serón, J., and Weintraub, A. Use of or systems in the chilean forest industries. *Interfaces*, 29(1):7–29, 1999. doi:10.1287/inte.29.1.7.

Epstein, R., Karlsson, J., Rönnqvist, M., and Weintraub, A. Harvest operational models in forestry. In Weintraub, A., Romero, C., Bjørndal, T., Epstein, R., and Miranda, J., editors, *Handbook Of Operations Research In Natural Resources*, volume 99 of *International Series In Operations Research amp; Mana*, pages 365–377. Springer US, 2007a. doi:10.1007/978-0-387-71815-6_20.

Epstein, R., Rönnqvist, M., and Weintraub, A. Forest transportation. In Weintraub, A., Romero, C., Bjørndal, T., Epstein, R., and Miranda, J., editors, *Handbook Of Operations Research In Natural Resources*, volume 99 of *International Series In Operations Research amp; Mana*, pages 391–403. Springer US, 2007b. doi:10.1007/978-0-387-71815-6_20.

Feillet, D., Dejax, P., Gendreau, M., and Gueguen, C. An exact algorithm for the elementary shortest path problem with resource constraints: Application to some vehicle routing problems. *Networks*, 44(3):216–229, 2004. doi:10.1002/net.20033.

Flisberg, P., Lidén, B., and Rönnqvist, M. A hybrid method based on linear programming and tabu search for routing of logging trucks. *Computers & Operations Research*, 36(4):1122–1144, 2009. doi:10.1016/j.cor.2007.12.012.

Forsberg, M., Frisk, M., and Rönnqvist, M. Flowopt – a decision support tool for strategic and tactical transportation planning in forestry. *International Journal of Forest Engineering*, 16(2):101–114, 2005. doi:10.1080/14942119.2005.10702519.

FPInnovations. `http://www.fpinnovations.ca`. Accessed October 13, 2014.

FPInterface. `http://www.fpsuite.ca/l_en/fpinterface.html`. Accessed October 13, 2014.

Frisk, M., Göthe-Lundgren, M., Jörnsten, K., and Rönnqvist, M. Cost allocation in collaborative forest transportation. *European Journal of Operational Research*, 205(2):448–458, 2010. doi:10.1016/j.ejor.2010.01.015.

Fukasawa, R., Longo, H., Lysgaard, J., de Aragão, M., Reis, M., Uchoa, E., and Werneck, R. Robust branch-and-cut-and-price for the capacitated vehicle routing problem. *Mathematical Programming*, 106(3):491–511, 2006. doi:10.1007/s10107-005-0644-x.

Garey, M. and Johnson, D. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. W.H. Freeman & Co., New York, NY, USA, 1979.

Gémieux, G. Planification de la récolte et allocation des produits aux usines. Msc thesis, Université de Montréal, August 2009. `http://hdl.handle.net/1866/3515`.

Gendreau, M., Hertz, A., and Laporte, G. A tabu search heuristic for the vehicle routing problem. *Management Science*, 40(10):1276–1290, 1994. doi:10.1287/mnsc.40.10.1276.

Gendreau, M., Laporte, G., Musaraganyi, C., and Taillard, É. A tabu search heuristic for the heterogeneous fleet vehicle routing problem. *Computers & Operations Research*, 26(12): 1153–1173, 1999. doi:10.1016/S0305-0548(98)00100-2.

Gerasimov, Y., Sokolov, A., and Fjeld, D. Improving cut-to-length operations management in russian logging companies using a new decision support system. *Baltic Forestry*, 19(1): 89–105, 2013.

Gingras, C., Cordeau, J.-F., and Laporte, G. Un algorithme de minimisation du transport à vide appliqué à l'industrie forestière. *INFOR: Information Systems and Operational Research*, 45(1):41–47, 2007. doi:10.3138/infor.45.1.41.

Glover, F. and Laguna, M. *Tabu Search*. Springer, New York, NY, USA, 1999.

Golden, B., Assad, A., Levy, L., and Gheysens, F. The fleet size and mix vehicle routing problem. *Computers & Operations Research*, 11(1):49–66, 1984. doi:10.1016/0305-0548(84)90007-8.

Gronalt, M. and Hirsch, P. Log-truck scheduling with a tabu search strategy. In Doerner, K., Gendreau, M., Greistorfer, P., Gutjahr, W., Hartl, R., and Reimann, M., editors, *Metaheuristics*, volume 39 of *Operations Research/Computer Science Interfaces Series*, pages 65–88. Springer US, 2007. doi:10.1007/978-0-387-71921-4_4.

Gurobi Optimization. Gurobi optimizer. `http://www.gurobi.com/`. Accessed April 27, 2014.

Hempsch, C. and Irnich, S. Vehicle routing problems with inter-tour resource constraints. In Golden, B., Raghavan, S., and Wasil, E., editors, *The Vehicle Routing Problem: Latest Advances and New Challenges*, volume 43 of *Operations Research/Computer Science Interfaces*, pages 421–444. Springer US, 2008. doi:10.1007/978-0-387-77778-8_19.

Ho, S. and Haugland, D. A tabu search heuristic for the vehicle routing problem with time windows and split deliveries. *Computers & Operations Research*, 31(12):1947–1964, 2004. doi:10.1016/S0305-0548(03)00155-2.

Karlsson, J., Rönnqvist, M., and Bergström, J. Short-term harvest planning including scheduling of harvest crews. *International Transactions in Operational Research*, 10(5): 413–431, 2003. doi:10.1111/1475-3995.00419.

Karlsson, J., Rönnqvist, M., and Bergström, J. An optimization model for annual harvest planning. *Canadian Journal of Forest Research*, 34(8):1747–1754, 2004. doi:10.1139/x04-043.

Kontoravdis, G. and Bard, J. A grasp for the vehicle routing problem with time windows. *ORSA Journal on Computing*, 7(1):10–23, 1995. doi:10.1287/ijoc.7.1.10.

Laporte, G. Fifty years of vehicle routing. *Transportation Science*, 43(4):408–416, 2009. doi:10.1287/trsc.1090.0301.

Laporte, G., Nobert, Y., and Desrochers, M. Optimal routing under capacity and distance restrictions. *Operations Research*, 33(5):1050–1073, 1985. doi:10.1287/opre.33.5.1050.

Letchford, A., Eglese, R., and Lysgaard, J. Multistars, partial multistars and the capacitated vehicle routing problem. *Mathematical Programming*, 94(1):21–40, 2002. doi:10.1007/s10107-002-0336-8.

Lysgaard, J., Letchford, A., and Eglese, R. A new branch-and-cut algorithm for the capacitated vehicle routing problem. *Mathematical Programming*, 100(2):423–445, 2004. doi:10.1007/s10107-003-0481-8.

McDonald, T., Haridass, K., and Valenzuela, J. Mileage savings from optimization of coordinated trucking. In *33rd Council on Forest Engineering Annual Meeting*, pages 1–11, Auburn, AL, USA, June 2010. `http://web1.cnre.vt.edu/forestry/cofe/documents/2010/McDonald_Transport.pdf`.

Michel, S. and Vanderbeck, F. A column-generation based tactical planning method for inventory routing. *Operations Research*, 60(2):382–397, 2012. doi:10.1287/opre.1110.1015.

Mitchell, S. *Operational forest harvest scheduling optimisation: A mathematical model and solution strategy*. PhD thesis, University of Auckland, December 2004. `http://hdl.handle.net/2292/1761`.

Moura, A. and Scaraficci, R. Hybrid heuristic strategies for planning and scheduling forest harvest and transportation activities. In *11th IEEE International Conference on Computational Science and Engineering, 2008. CSE'08.*, pages 447–454, July 2008. doi:10.1109/CSE.2008.31.

Natural Resources Canada. http://www.nrcan-rncan.gc.ca. Accessed October 13, 2014.

Neame, P. *Nonsmooth methods in integer programming*. PhD thesis, University of Melbourne, March 1999.

Palmgren, M., Rönnqvist, M., and Värbrand, P. A solution approach for log truck scheduling based on composite pricing and branch and bound. *International Transactions in Operational Research*, 10(5):433–447, 2003. doi:10.1111/1475-3995.00420.

Palmgren, M., Rönnqvist, M., and Värbrand, P. A near-exact method for solving the log-truck scheduling problem. *International Transactions in Operational Research*, 11(4): 447–464, 2004. doi:10.1111/j.1475-3995.2004.00469.x.

Pisinger, D. and Ropke, S. A general heuristic for vehicle routing problems. *Computers & Operations Research*, 34(8):2403–2435, 2007. doi:10.1016/j.cor.2005.09.012.

Prescott-Gagnon, E., Desaulniers, G., and Rousseau, L.-M. A branch-and-price-based large neighborhood search algorithm for the vehicle routing problem with time windows. *Networks*, 54(4):190–204, 2009. doi:10.1002/net.20332.

Ramkumar, N., Subramanian, P., Narendran, T., and Ganesh, K. Mixed integer linear programming model for multi-commodity multi-depot inventory routing problem. *OPSEARCH*, 49(4):413–429, 2012. doi:10.1007/s12597-012-0087-0.

Rey, P., Muñoz, J., and Weintraub, A. A column generation model for truck routing in the chilean forest industry. *Information Systems and Operational Research*, 47(3):215–221, 2009. doi:10.3138/infor.47.3.215.

Rix, G., Rousseau, L.-M., and Pesant, G. Solving a multi-period log-truck scheduling problem with column generation. In *34th Council on Forest Engineering Annual Meeting*, Québec, QC, Canada, June 2011. https://www.cirrelt.ca/cofe2011/proceedings/29-rix.pdf.

Rix, G., Rousseau, L.-M., and Pesant, G. A column generation algorithm for tactical timber transportation planning. Technical Report CIRRELT-2013-40, CIRRELT, July 2013. https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2013-40.pdf.

Rix, G., Rousseau, L.-M., and Pesant, G. A transportation-driven approach to annual harvest planning. Technical Report CIRRELT-2014-24, CIRRELT, May 2014. https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2014-24.pdf.

Rix, G., Rousseau, L.-M., and Pesant, G. A column generation algorithm for tactical timber transportation planning. *Journal of the Operational Research Society*, 66(2):278–287, 2015. doi:10.1057/jors.2013.170.

Rönnqvist, M. Optimization in forestry. *Mathematical Programming*, 97(1-2):267–284, 2003. doi:10.1007/s10107-003-0444-0.

Ropke, S., Cordeau, J.-F., and Laporte, G. Models and branch-and-cut algorithms for pickup and delivery problems with time windows. *Networks*, 49(4):258–272, 2007. doi:10.1002/net.20177.

Rousseau, L.-M., Gendreau, M., and Feillet, D. Interior point stabilization for column generation. *Operations Research Letters*, 35(5):660–668, 2007. doi:10.1016/j.orl.2006.11.004.

Rummukainen, H., Kinnari, T., and Laakso, M. Optimization of wood transportation. In *Papermaking Research Symposium*, pages 1–10, June 2009. `http://www.vtt.fi/inf/julkaisut/muut/2009/PRS2009.pdf`.

Salazar-Aguilar, M., Langevin, A., and Laporte, G. Synchronized arc routing for snow plowing operations. *Computers & Operations Research*, 39(7):1432–1440, 2012. doi:10.1016/j.cor.2011.08.014.

Toth, P. and Vigo, D. *The Vehicle Routing Problem*. Siam, Philadelphia, PA, USA, 2001.

Van Anholt, R., Coelho, L., Laporte, G., and Vis, I. An inventory-routing problem with pickups and deliveries arising in the replenishment of automated teller machines. Technical Report CIRRELT-2013-71, CIRRELT, November 2013. `https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2013-71.pdf`.

Weintraub, A., Epstein, R., Morales, R., Seron, J., and Traverso, P. A truck scheduling system improves efficiency in the forest industries. *Interfaces*, 26(4):1–12, 1996. doi:10.1287/inte.26.4.1.

Xu, H., Chen, Z.-L., Rajagopal, S., and Arunapuram, S. Solving a practical pickup and delivery problem. *Transportation Science*, 37(3):347–364, 2003. doi:10.1287/trsc.37.3.347.16044.